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Artificial Intelligence-Related Digital Skills and Employment Outcomes for Underrepresented Women

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Abstract

This study examines whether signalling AI-related digital skills improves employment outcomes for women from underrepresented groups in England, defined by race, age, sexual orientation, and autism-spectrum disclosure. Using correspondence evidence, the study finds that underrepresented women receive fewer interview invitations and are considered for lower-paid vacancies than majority-group women. In pooled analyses, signalling AI-related digital skills increases interview invitations for underrepresented applicants, but does not eliminate the disadvantage. These findings are consistent with AI Capital and productivity-signalling frameworks, as employers appear to value AI-related capabilities while the returns to such credentials remain constrained by persistent demographic inequalities. The study therefore shows that positive returns to AI-related skills and labour-market disadvantage can coexist. Its broader implication is that digital upskilling can strengthen the recruitment prospects of underrepresented women, but cannot by itself deliver parity in employment outcomes. A dual policy response is therefore required, combining wider and more equitable access to AI education and training with stronger anti-discrimination enforcement, greater transparency in shortlisting, improved oversight of recruitment processes, and systematic evaluation of how employers recognise applicant credentials. The study contributes to the economics of AI by linking correspondence evidence to the AI Capital framework and highlighting barriers to converting AI-related resources into meaningful employment opportunities.

JEL classification

J71, J24, J31, J64, C93, J15, J16, J14, O33, M51

Keywords

AI Capital, artificial intelligence, skills, discrimination, hiring, wages, sexual orientation, race, age, autism spectrum

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1. Introduction

Studies have repeatedly documented unequal access to employment and wage-related opportunities across demographic groups on the basis of race, age, sexual orientation and disability (Lippens et al., 2023; Batinovic et al., 2023; Iwasaki and Satogami, 2023; Flage, 2020; Baert, 2018; Zschirnt and Ruedin, 2016; Drydakis, 2009). A related strand of this literature examines whether observable signals of applicant quality or productivity shape employer responses during recruitment (Veit et al., 2022; Fossati et al., 2020; Bertrand and Mullainathan, 2004). This study contributes to that empirical strand by examining whether signalling AI-related digital skills improves hiring outcomes for women from underrepresented groups. Existing research on AI and hiring often focuses on algorithmic bias within AI-assisted screening systems (Chen, 2023), while less is known about how employers respond to applicants who present AI-related digital skills as part of their profile. Governments, employers and training providers increasingly promote digital upskilling, with AI-related digital-skills training forming part of these efforts, as a route to improving labour-market inclusion (Kyriakidou et al., 2025; Rigley et al., 2024; Cramarenco et al., 2023; Pagani et al., 2023; Georgieff and Hyee, 2022). This raises a practical empirical question about whether employers respond to AI-related digital skills signals from underrepresented applicants in ways consistent with a productivity-signalling interpretation and whether such signals increase their chances of receiving interview invitations.

The study examines this question using a correspondence design in the London labour market in 2025. The analysis focuses on women because hiring outcomes continue to be shaped by gendered disadvantage across occupations and wage structures (Heilman et al., 2024; Galos and Coppock, 2023; Iwasaki and Satogami, 2023). Evidence also indicates that gendered bias can interact with racism, ageism, heterosexism and disability-related stigma during recruitment, intensifying disadvantage at the shortlisting stage (Drydakis et al., 2023). Focusing on women from underrepresented groups therefore provides a stringent setting for assessing whether a salient productivity signal improves employer responses to applicants who may otherwise face disadvantage in hiring. The correspondence design follows established practice in the field (Lippens et al., 2023; Veit et al., 2022; Fossati et al., 2020; Bertrand and Mullainathan, 2004; Riach and Rich, 2002). Fictional job applications are submitted to real vacancies while all characteristics apart from the treatments of interest are held constant, allowing differences in employer responses to be attributed to experimentally varied applicant signals (Riach and Rich, 2002). In this study, applications are submitted by three types of applicants. These are majority-group women without an

AI-related digital skills signal, underrepresented women without the signal, and underrepresented women with the signal.

The design identifies two causal quantities. First, the comparison between majority-group women without the AI-related digital skills signal and underrepresented women without the signal estimates the baseline interview invitation gap associated with the underrepresentation status signal. Second, the comparison between underrepresented women with and without the AI-related digital skills signal estimates the interview invitation uplift among underrepresented applicants due to the AI-related digital skills signal. These are the quantities the design is suited to estimate because both the underrepresentation status signal and the AI-related digital skills signal are experimentally assigned. The design does not include majority-group women with an AI-related digital skills signal. It therefore cannot estimate whether the return to the AI-related digital skills signal differs between majority and underrepresented applicants, nor can it identify a causal reduction in discrimination in the strict sense. The analysis is consequently framed around the gain to underrepresented women from signalling AI-related digital skills and around how their resulting interview invitation outcomes compare with the observed majority no-AI-related-digital-skills comparator. This comparator is relevant in non-graduate, mid-level vocational recruitment contexts where formal AI-related credentials remain unevenly distributed and are not yet universal among the labour force (Vasilescu et al., 2020).

In this study, “AI-related digital skills” refers to applied competencies involving the practical use of AI-enabled workplace tools, such as automated processing systems, AI-assisted platforms and sector-specific digital workflows (Squicciarini and Nachtigall, 2021). Conceptually, these competencies can be situated within the AI Capital framework (Drydakis, 2024), which treats AI-related knowledge, skills and capabilities as productive resources that may enhance labour-market outcomes and operate as signals of applicant productivity. Because the comparison applicants hold nondigital certifications, the design can identify whether employers respond to an AI-related digital-skills signal relative to a nondigital credential. Employers may nevertheless interpret the credential not only as evidence of AI-specific expertise but also as a signal of broader digital literacy, adaptability or technological confidence (Shiri, 2024; Squicciarini and Nachtigall, 2021). The framing is therefore deliberately conservative. AI-related digital skills are examined as an empirically relevant digital productivity signal, without assuming that they constitute a uniquely distinct category of digital skill. Without a separate non-AI digital-skills condition, the experiment cannot determine whether any observed response is specific to AI-related competence or reflects broader digital literacy.

The relevance of this study is reinforced by the emerging UK skills-policy context. Skills England’s 2026 UK Standard Skills Classification (Skills England, 2026) provides a national framework for mapping digital literacy occupational skills, tasks, knowledge, qualifications and jobs. The classification identifies as a core skill and includes "using and developing AI tools" within the domain of programming and implementing digital tools and systems. This policy context strengthens the rationale for studying whether AI-related digital skills development through training can improve occupational access for underrepresented groups. If AI skills are becoming embedded in the national skills-classification framework through which occupational readiness is defined, it is important to evaluate whether signalling such skills improves recruitment outcomes for applicants who have historically faced barriers at the shortlisting stage.

The study makes three contributions. It provides field-experimental evidence on how employers respond when applicants present AI-related digital skills during standard recruitment. This is particularly important because AI-enabled tools are changing task requirements, while groups already facing recruitment barriers may risk further disadvantage if access to emerging digital skills is uneven. The four underrepresented groups examined in the study have each been associated with labour market disadvantage in prior research. Examining whether an AI-related digital skills signal improves their early-stage recruitment outcomes is therefore relevant to debates on technological change, training policy and access to occupations.

The study also identifies two causal comparisons, namely the baseline interview-invitation gap faced by underrepresented women and the gain in interview invitations associated with signalling AI-related digital skills acquired through training among those applicants. Evaluating whether signalling AI-related training and skills can function as an inclusion strategy requires evidence on whether the signal improves shortlisting outcomes in real recruitment settings, and whether any improvement is sufficient to move applicants closer to the majority no-AI comparator. The study also considers variance-based interpretations linked to the Heckman–Siegelman critique (Heckman and Siegelman, 1993). This part of the analysis is treated as a model-based sensitivity check. Because the design does not include independent variation in signal precision, it cannot provide a definitive test of employer beliefs, perceived productivity dispersion or discrimination mechanisms. The contribution is therefore deliberately focused. The study estimates whether signalling AI-related digital skills generates an interview-invitation return for underrepresented women, while recognising that training interventions should be considered alongside the wider recruitment barriers that continue to shape access to work.

The findings indicate that underrepresented women receive fewer interview invitations and are invited to lower-paid vacancies relative to majority-group women. Signalling AI-related digital skills improves interview invitation outcomes for underrepresented women in the pooled analysis and moves them closer to the observed majority no-AI comparator, although disadvantage remains. The results are consistent with an interpretation in which AI-related digital skills operate as productivity signals valued in labour-market screening, while also demonstrating that such signals remain insufficient to eliminate hiring disadvantage. These findings provide field-experimental evidence consistent with the AI Capital framework (Drydakis, 2024), insofar as they show that signalling AI-related skills acquired through training can generate returns at the recruitment stage. At the same time, the persistence of disadvantage among underrepresented applicants who signal such skills indicates that signalling AI Capital alone is insufficient to overcome wider barriers in recruitment. The study does not claim that AI-related digital skills reduce discrimination or narrow discriminatory gaps in a strict causal sense. The variance-based analysis is interpreted cautiously and does not provide definitive evidence on employer beliefs or variance-based discrimination. Without a majority-group applicant with the same AI-related digital skills signal, the design cannot determine whether majority and underrepresented applicants receive equivalent, smaller or larger returns to the signal. The findings therefore call for a dual policy response that widens equitable access to AI-related education and training, enabling underrepresented groups to develop and signal labour-market-relevant AI Capital, while also addressing the recruitment barriers that may limit the returns to that capital. Training and education policies should therefore be complemented by stronger anti-discrimination enforcement, greater transparency in shortlisting practices, improved oversight of recruitment processes and systematic evaluation of how applicant credentials are recognised by employers.

The remainder of the study is structured as follows. Section 2 outlines the conceptual background, focusing on productivity signalling and economic models of discrimination as interpretive frameworks, and explains the variance-based concern. Section 3 describes the experimental setting and research design. Section 4 presents descriptive evidence on interview invitations and wage sorting. Section 5 reports the econometric estimates and sensitivity analyses. Section 6 discusses the implications, limitations and policy relevance. Section 7 concludes.

2. Theoretical reflections

International review studies indicate that AI is associated with both the displacement of routine and highly automatable tasks and the creation of new roles requiring advanced digital and analytical competencies (Rigley et al., 2024; Drydakis, 2024; Cramarenco et al., 2023; Georgieff and Hyee, 2022). The diffusion of AI-enabled technologies has expanded employer demand for digital skills across a wide range of occupations, particularly in roles that combine technical expertise with problem-solving, communication and continuous learning (Kyriakidou et al., 2025; Pagani et al., 2023; Georgieff and Hyee, 2022). Although automation may reduce employment opportunities in some areas, technological adoption and organisational restructuring are also associated with new forms of work in which applicants are expected to adapt to changing digital systems (Kyriakidou et al., 2025; Cramarenco et al., 2023; Pagani et al., 2023). In this context, AI-related digital skills may become salient indicators of labour-market readiness.

Human capital theory (Becker, 1964) conceptualises education and training as productivity-enhancing investments associated with improved employability and earnings (Deming, 2022; Kessler and Lülfesmann, 2006; Black and Lynch, 1996). During recruitment, however, employers do not observe productivity directly. They rely on credentials and other visible indicators when forming expectations about applicants. Signalling theory (Spence, 1973; Weiss, 1995) therefore provides a useful framework for understanding how educational credentials and specialised skills communicate information about ability, motivation and adaptability under uncertainty (Connelly et al., 2025; Pericles Rospigliosi et al., 2014). Within the correspondence-study literature, a related strand examines whether observable indicators of applicant quality shape employer responses to otherwise comparable candidates (Veit et al., 2022; Fossati et al., 2020; Bertrand and Mullainathan, 2004).

The AI Capital framework offers a complementary perspective on this process by conceptualising AI-related knowledge, skills and capabilities as forms of productive and signalling capital that applicants can mobilise when entering labour markets shaped by digital transformation (Drydakis, 2024). Existing evidence suggests that AI Capital is associated with improved access to occupations, employment prospects and earnings, making it particularly relevant to debates on training, inclusion and labour-market mobility for underrepresented groups (Drydakis, 2024). This study situates AI-related digital skills within this broader signalling framework. The signal is not treated as a unique or fully separable form of human capital. Employers may interpret it as evidence of applied AI competence, broader digital literacy, technological adaptability or familiarity with AI-enabled workplace tools. The empirical question is therefore whether such a signal improves interview invitation outcomes for underrepresented women and how their resulting outcomes compare with the observed majority no-AI comparator.

Although productivity signals may shape recruitment decisions, extensive empirical evidence shows that unequal treatment continues to structure labour-market outcomes across demographic groups (Lippens et al., 2023; Batinovic et al., 2023; Iwasaki and Satogami, 2023). Several theoretical accounts help interpret such patterns. Becker's (1957) account of taste-based discrimination proposes that employers, co-workers or customers may hold negative preferences towards certain groups, creating perceived costs that affect hiring decisions even when applicants possess comparable qualifications. In a recruitment setting, this mechanism implies that an applicant from a discriminated-against group may effectively need to demonstrate higher expected productivity to receive the same favourable hiring response as an otherwise comparable majority-group applicant. Statistical discrimination theory emphasises decision-making under uncertainty

(Arrow, 1973; Phelps, 1972). Employers may rely on perceived group averages, stereotypes or prior beliefs when individual productivity is difficult to observe directly. Historical inequalities and group-based expectations may therefore shape hiring outcomes even in the absence of explicit hostility. Observable credentials may improve outcomes if employers update their beliefs in response to credible information about skills. Yet unequal outcomes may persist if prior expectations remain influential or if new information is interpreted unevenly across groups. These mechanisms are conceptually distinct, but they can generate similar empirical patterns in a correspondence design. An observed interviews invitation uplift for underrepresented applicants who signal AI-related digital skills could be consistent with several channels. The signal may reduce uncertainty about productivity. It may be valued as evidence of adaptability in technology-mediated work. It may also partly compensate for a group-based penalty without changing the underlying preferences or beliefs that generate disadvantage. For this reason, the study uses taste-based and statistical discrimination theories as interpretive lenses. It does not claim to distinguish decisively between them.

A related concern arises from the Heckman–Siegelman critique. Heckman and Siegelman (1993) highlight that variation in interview invitation rates may reflect not only mean employer evaluations, but also the variance of unobserved productivity or perceived signal precision across groups. If employers compare latent perceived productivity with a hiring threshold, group differences in dispersion can affect interview invitation probabilities. Empirical studies report mixed evidence on the relevance of this variance-based concern in correspondence designs (Granberg et al., 2020; Baert, 2015; Carlsson et al., 2014). In the present study, the variance-based analysis is treated as a diagnostic sensitivity exercise because the design does not include independent variation in the precision of applicant signals and cannot provide a definitive test of employer beliefs. The theoretical framework therefore supports a cautious interpretation of the evidence. Improvements in interview invitation outcomes for underrepresented women signalling AI-related digital skills are interpreted as an AI-related invitation uplift, not as proof that discrimination has declined. The design can show whether underrepresented applicants benefit from presenting the signal and whether their outcomes move closer to the majority no-AI comparator. It cannot establish whether the signal changes discriminatory preferences, revises statistical beliefs, alters perceived risk or generates a general productivity premium that would also apply to majority applicants.

3. Experimental setting

This section outlines the design and implementation of the four correspondence tests conducted in London. It begins by presenting the applicants' profiles and the signalling methods used to indicate race, age, sexual orientation and autism spectrum disclosure (Section 3.1). It then describes the sectors and job openings to which applications were submitted, together with the allocation of sector-relevant skills (Section 3.2). The following subsections explain how AI-related digital skills were signalled in the treatment group through an AI-related certificate, sector-specific training descriptions and associated AI-skills references in the CV (Section 3.3), and how the experimental materials were assessed during the pre-test phase (Section 3.4). The section concludes by detailing the procedures for sending applications, recording employer responses and collecting firm-level information such as equality policies, firm size and wage data (Section 3.5).

3.1 Applicants' profiles: General characteristics

For each job opening, three matched applications were submitted to the same firm: one from a majority-group applicant without the AI-related digital skills signal, referred to as control group one; one from an underrepresented applicant without the AI-related digital skills signal, referred to as control group two; and one from an underrepresented applicant with the AI-related digital skills signal, referred to as the treatment group. The study comprises four distinct matched groups corresponding to the four experiments. In the race experiment, the matched group consisted of a White British woman without the AI-related digital skills signal, a Black British woman without the signal, and a Black British woman with the signal. In the age experiment, the matched group consisted of a younger White British woman without the signal, an older White British woman without the signal, and an older White British woman with the signal. In the sexual orientation experiment, the matched group consisted of a heterosexual White British woman without the signal, a lesbian White British woman without the signal, and a lesbian White British woman with the signal. In the autism-spectrum disclosure experiment, the matched group comprised three profiles. These were a White British woman with neither an autism-spectrum disclosure nor an AI-related digital-skills signal, a White British woman with an autism-spectrum disclosure but without the signal, and a White British woman with both an autism-spectrum disclosure and the signal.

All applicants were native speakers. The age experiment included two female profiles, aged 28 and 50. The 28-year-old applicants had eight years of experience following the completion of their studies, working in roles aligned with their education, apprenticeships and occupational specialisms. In the age experiment, the 50-year-old applicants were presented with experience across six employers, each held for four to five consecutive years, reflecting a realistic long-term employment history while maintaining comparability in job relevance. The CVs did not include any information regarding children, parental status, caregiving responsibilities or parental leave history. This decision was intended to minimise additional signals that might introduce unintended variation across profiles. However, employers may still form implicit assumptions about the likelihood of pregnancy or caregiving roles based on age or sexual orientation cues. The experimental design cannot disentangle these inferences. Accordingly, outcomes in the age and sexual orientation experiments should be interpreted as reflecting employer responses to the broader set of signals associated with each profile, alongside possible assumptions related to fertility or motherhood expectations. This reflects real-world hiring contexts in which multiple stereotypes may operate simultaneously.

All applicants held BTEC Level 3 qualifications relevant to their occupational sector, not university degrees. BTEC Level 3 qualifications provide applied, practical and vocational training in areas such as business, IT, customer service, administration, hospitality, social care, logistics, and digital or creative work, and align with mid-level job requirements. Learners aged 16–18 who meet the entry requirements, usually GCSEs, can access these qualifications. All applicants also completed a one-year apprenticeship with an employer as part of their BTEC Level 3 programme.

The decision to focus on applicants with Level 3 qualifications reflects the study's emphasis on vocational and non-graduate recruitment routes. Data from the ONS Annual Population Survey reported through Nomis show that, in 2025, 13.3 per cent of London residents aged 16–64 had a Regulated Qualifications Framework (RQF) Level 3 qualification as their highest qualification, while 63.7 per cent held qualifications at RQF Level 4 or above (ONS, 2026). The experimental profiles therefore represent a specific segment of the London labour market and should not be interpreted as representative of the educational profile of working-age Londoners as a whole. Focusing on Level 3 vocational profiles is nevertheless policy relevant for occupations in which BTEC qualifications, apprenticeships and other applied training routes provide pathways into employment. At the same time, the focus on London-based private-sector vacancies and mid-level vocational roles defines the empirical scope of the analysis. The findings should therefore be interpreted within this specific labour-market context and should not be assumed to generalise across all labour-market settings.

School and employer addresses were selected to avoid implying different socioeconomic backgrounds. Each applicant had a mobile telephone number, a postal address and an email address. Information relating to schools, apprenticeships, employers and home addresses was rotated across applications within each experiment to prevent the introduction of systematic differences that could bias the experimental setting. Apart from the intended demographic, disclosure and AI-related manipulations, applicants reported the same baseline leisure interests, namely travelling and cinema, and the same baseline personal descriptors, namely efficient and creative. In the sexual orientation experiment, the leisure interests were kept the same, while the partner cue varied only to signal sexual orientation.

3.1.a Race experiment

In the race experiment, all three applicants were described as British women aged 28 years, with both nationality and age explicitly stated in the CVs. Race was signalled through a self-identification field in the personal details section, consistent with established correspondence-testing practices that use realistic but unobtrusive cues to indicate group membership (Baert, 2018). The majority-group applicant without AI-related digital skills identified as White British, whereas the underrepresented applicants without and with AI-related digital skills identified as Black British. Apart from the racial identification and the AI-related digital skills signal included in the treatment CVs, all other information was held constant across the three profiles.

3.1.b Age experiment

In the age experiment, all three applicants were White British women, and this characteristic was explicitly stated in the CVs. Age was signalled through a combination of date of birth, education timing and employment history, consistent with standard practice in age-related correspondence studies (Batinovic et al., 2023). The younger majority-group applicant without AI-related digital skills was described as 28 years old and born in 1997, while the older underrepresented applicants without and with AI-related digital skills were described as 50 years old and born in 1975. Education and employment dates were aligned with these birth years, ensuring that the younger applicant presented a shorter employment history and the older applicants a longer, continuous record. Apart from these age-related signals and the AI-related digital skills entries included in the treatment CVs, all other characteristics were comparable.

3.1.c Sexual orientation experiment

In the sexual orientation experiment, all three applicants were White British women aged 28 years, with nationality, race and age explicitly stated in the CVs. Sexual orientation was signalled through the personal-interests section, following established approaches in the literature that use naturalistic references to partners with gendered names (Flage, 2020). The heterosexual applicant indicated that she enjoyed travelling and going to the cinema with her partner, using male names such as George and Peter. The two lesbian applicants, without and with AI-related digital skills respectively, indicated that they enjoyed travelling and going to the cinema with their partners, using female names such as Helen and Sonia. For example, one heterosexual entry stated: “I enjoy travelling at weekends with my partner, George,” while one lesbian entry stated: “I enjoy travelling at weekends with my partner, Helen.” To avoid systematic differences across profiles, the wording of these signals was paraphrased and rotated. Apart from these sexual orientation cues and the AI-related digital skills entries included in the treatment CVs, all other information across the three applications was identical.

3.1.d Autism-spectrum disclosure experiment

In the autism-spectrum disclosure experiment, all three applicants were White British women aged 28 years, and these characteristics were explicitly stated in the CVs. Autism-spectrum status was signalled through brief disclosure statements in the personal-profile section, consistent with established correspondence-testing approaches that use realistic, strengths-based self-descriptions to indicate disability (Bjørnshagen and Ugreninov, 2021). Although the broader concept of neurodivergence encompasses a range of conditions (e.g. ADHD, dyslexia and related differences), the experimental design in this study focuses specifically on autism-spectrum identity. The findings should therefore be interpreted as reflecting employer responses to autism disclosure, not neurodivergence more broadly.

For the underrepresented applicants without and with AI-related digital skills, short statements in the CV indicated that the applicants were on the autism spectrum and included references to associated strengths, such as strong focus. For example, one disclosure stated: "I am on the autism spectrum and known for my strong focus and attention to detail." The wording of these disclosures was paraphrased and rotated across the two autism spectrum applications to avoid systematic bias. Apart from these disclosure statements and the AI-related digital skills entries in the treatment CVs, all other aspects of the profiles were identical.

The autism spectrum disclosure signal included strengths-based statements referencing characteristics such as strong focus and attention to detail (Fitch et al. 2015; Baron-Cohen et al., 2009). This approach reflects contemporary disclosure practices in which individuals frequently frame autistic identity alongside capabilities and work-relevant strengths, thereby enhancing ecological validity. However, this design introduces a construct-validity consideration because the disclosure simultaneously signals group membership and potentially favourable productivity-related attributes. As a result, the treatment profile may contain additional productivity signals not explicitly present in control applications. Any observed penalty associated with autism spectrum disclosure should therefore be interpreted cautiously, as positive capability cues may attenuate negative employer responses and lead to conservative estimates of disadvantage.

3.2 Sectors, Job Openings and Skills

The applicants applied for roles aligned with their studies and with their previous and current employment histories in London. The study focused on private-sector vacancies. In the UK, the public sector accounts for approximately 18 per cent of the total workforce, while the private sector employs more than four times as many people (ONS, 2025). Focusing on private-sector openings therefore reflects the labour market conditions encountered by many job-seekers and increases the relevance of the findings. All applications were submitted to full-time positions in which a university degree was not listed as a requirement. Vacancies were identified through a random sample of advertisements appearing on leading UK job-search websites. The widespread use of these platforms suggests that they represent a typical resource for job-seekers.

The correspondence experiments focused on ten sectors. **Supplementary Table S1** presents the sectors in Panel I, the percentage of applications submitted to each sector in Panel II, the nature of job openings within each sector in Panel III, and the work tasks reported in the applicants' CVs in Panel IV. Within each sector, all applicants reported the same set of work tasks. For illustration, in the finance and payment processing sector, all CVs included tasks related to invoice preparation, bookkeeping processes, financial-record organisation and payment tracking. These tasks were paraphrased while retaining the same meaning and were rotated across applications. This rotation ensured that all applicants demonstrated sector-relevant skills without systematically linking particular tasks to specific demographic characteristics.

3.3 AI-Related Digital Skills Signalling

Each submission comprised an email message, an attached application letter and a CV. The email briefly informed recruiters that the applicant was applying for the vacancy and that the relevant documents were attached. The application letter stated that the applicant had seen the announcement for the position, expressed interest in the role and provided a targeted summary of relevant experience. The CV presented a full employment history.

For the underrepresented applicants with AI-related digital skills, the signal was conveyed through a sector-specific AI certificate included in the training section of their CVs. The CV stated that this was a six-month training programme completed in 2024. The certificate entry was followed by a short description of the training and the skills developed. Such programmes are widely available in the UK and are offered by both public and private providers (Drydakis, 2025a; 2025b), and similar forms of signalling are frequently used in correspondence tests examining employer responses to applicant quality signals (Baraku and Busetta, 2025; Lippens et al., 2022). As shown in **Supplementary Table S2**, these descriptions emphasised practical exposure to workplace AI technologies within each sector to ensure that the training appeared credible, appropriately scoped and aligned with sector-specific job tasks. The accompanying list of AI-related digital skills was designed to ensure consistent signalling and to provide employers with a clear and sector-relevant indication of the applicant's skills. The inclusion of this signal enables an assessment of whether employers respond to AI-related digital skills as meaningful evidence of competence, while recognising that the design cannot determine whether any response reflects taste-based discrimination, statistical discrimination, or other forms of employer screening.

The AI training was designed to resemble realistic workplace-oriented digital upskilling programmes. The content and framing of the certificate were aligned with routine digital workflows commonly associated with mid-level vocational roles, with less emphasis on advanced technical occupations (Margaryan, 2023; Shiohira, 2021). Training descriptions emphasised the automation of administrative tasks, AI-assisted data handling and integration with existing workplace software so that the credential plausibly reflected incremental technological capabilities relevant to the advertised positions. The experimental design therefore does not assume that employers were explicitly seeking AI expertise. Instead, the credential functions as a contemporary productivity signal that may indicate technological adaptability or improved efficiency in digitally mediated work environments. Employers may interpret the credential as evidence of broader digital competence or advanced digital literacy, as distinct from specialised AI development expertise. The experiment does not distinguish between these interpretations but evaluates employer responses to an additional productivity-related credential framed around AI-related digital skills, consistent with signalling theory, in which employer interpretation of observable credentials is central.

This interpretation is particularly relevant in the context of the occupations examined in this study. The targeted vacancies correspond to mid-level vocational roles in which tasks frequently involve routine digital workflows and software-mediated processes. Job descriptions often referred to activities such as electronic record management, customer relationship management systems, inventory tracking platforms, digital payment processing, scheduling software or administrative data handling. Within this context, the credential captures technological adaptability and productivity-related capabilities that may be valued even when AI is not an explicit requirement of the role. Such occupations provide a useful setting for examining these effects because technological change often occurs through the incremental integration of new tools into existing work practices. Employers may therefore interpret contemporary digital credentials as indicators of general productivity or adaptability, as distinct from specialised technical expertise.

For illustration, treatment-group applications in the Finance and Payment Processing sector included the following training entry, Certificate in AI for Financial Administration Support (2024). The description explained that the course introduced automated invoice-processing tools, AI-enabled receipt-reading systems and digital financial-record platforms. It further stated that the applicant had developed practical finance skills using such technologies, specifically by generating invoices through automated systems, reviewing and validating receipts with AI-supported scanners, entering financial information into AI-enhanced bookkeeping platforms and reconciling payment activity through accounting dashboards.

In addition to the AI-related digital skills signal used in the treatment group, the study incorporates a sector-oriented training programme for the majority and underrepresented women who did not present AI-related digital skills. This design ensures that the AI certificate does not inadvertently signal broader attributes unrelated to technological competence, such as motivation, conscientiousness or engagement in lifelong learning. Without a comparable training entry in the control applications, employers might interpret the presence of training itself, not the AI content, as evidence of higher commitment or effort. To address this concern, each control-group profile included a six-month certificate aligned with the relevant sector but unrelated to AI technologies. As shown in **Supplementary Table S3**, these programmes mirror the AI training in structure and duration and involve skills commonly associated with mid-level roles in each occupational field. For example, in the Finance and Payment Processing sector, the CVs of majority and underrepresented applicants without AI credentials listed a Certificate in Financial Administration Support (2024) covering invoice preparation, bookkeeping processes and financial-record organisation. The accompanying skills description indicated that applicants had developed workplace-ready finance competencies, such as preparing invoices for routine operations, carrying out daily bookkeeping tasks, maintaining organised financial files for business oversight and tracking payments to support accounting procedures.

This approach allows the study to distinguish employer responses to AI-related digital skills from responses to the presence of additional training more generally. The programmes used in the control group were intentionally occupation-oriented, with no focus on AI-related technologies. Such certificates provide realistic indications of occupational competence without implying digital or technological capabilities. In contrast, technology-focused training, even if unrelated to AI, could inadvertently signal broader digital ability or a predisposition towards technology adoption, thereby weakening the distinction between control and treatment conditions. The design therefore preserves a clear experimental contrast between general occupational credentials and AI-related digital skills, strengthening the internal validity of the study.

At the same time, this design shapes the interpretation of the results. Including a majority-group applicant with AI-related digital skills would allow estimation of interaction effects between group status and the AI-related digital skills signal and would show whether the signal carries similar or different returns across applicant groups. However, the present design focuses on comparing relative gaps across matched conditions, not on estimating the full causal return to AI-related digital skills training. Accordingly, the analysis evaluates whether observed disparities differ when the productivity signal is present, without attributing improvements exclusively to discrimination-reducing mechanisms.

Supplementary Table S4 presents samples of email communication (Panel I), application letters (Panel II) and CVs (Panel III) for the Finance and Payment Processing sector across the three applicant profiles used in the race experiment. The table illustrates the construction of the matched applications and clarifies how the experimental variation is embedded in the materials, allowing the study to examine employer responses to racial identity and whether AI-related digital skills modify observed shortlisting patterns.

3.4 Pre-Test Assessment of Experimental Materials

Before launching the four experiments, the research team conducted pre-tests to verify that the experimental signals were transparent and that productivity-related information was balanced across applicants in line with the design of each experiment. A screening questionnaire consisting of 40 closed and open questions was administered to HR professionals (n = 11), employers with recruitment responsibilities (n = 17), final-year university students with knowledge of labour markets (n = 36), and correspondence-test scholars (n = 7). Participants were shown job adverts together with the matched application sets for each experiment and sector under consideration. The pre-tests had four main objectives.

First, the exercise assessed whether the demographic predominantly cues for race, age, sexual orientation and autism spectrum status were correctly perceived. Manipulation checks asked participants to classify each applicant's race, age group, sexual orientation and autism spectrum status and to rate the clarity of these cues. The assessment examined whether the intended demographic category was recognised and whether the cues were considered clear. A priori, a version was retained only if at least 90 per cent of participants correctly recognised the intended demographic category. Clarity was assessed using three response options, "unclear", "ambiguous" and "clear". Versions were accepted only when the cues were rated as clear, with minimal indication of ambiguity or lack of clarity.

Second, the pre-tests evaluated the transparency and distinctiveness of the AI-related digital skills signal. Participants indicated whether they believed each applicant had completed the training, how clear this signal appeared, and whether the wording of the training descriptions suggested additional differences in motivation, conscientiousness or general digital ability. For the control-group CVs, the questionnaire examined whether the sector-oriented certificate was recognised as relevant training without being interpreted as AI or advanced digital training. This procedure enabled the research team to verify that the certificate was interpreted specifically as an AI-related signal, distinct from a generic marker of effort or engagement. Acceptance required that at least 90 per cent of participants correctly recognised the training as AI-related. In line with the pre-defined protocol, versions were excluded or revised if respondents attributed systematically higher motivation, conscientiousness or overall ability to treatment profiles beyond the intended productivity-related signal.

Third, the pre-tests examined whether the three profiles in each matched set were perceived as comparable in terms of productivity, work experience, personal descriptors and overall suitability, apart from the intended manipulations within each sector. Participants rated the realism of each application, perceived productivity, sectoral fit and writing quality. They also compared the three profiles and were asked explicitly whether they noticed any systematic differences beyond demographic group and AI training. For the age experiment, it was necessary to ensure that respondents recognised the greater work experience of the older applicants without interpreting this as an unintended advantage unrelated to the experimental design. Open-ended questions invited participants to identify any wording, structure or formatting that made one application appear stronger or weaker than the others.

Fourth, the pre-tests examined whether the fictional training providers were perceived as credible, realistic and comparable across applicants. Participants rated the legitimacy of the provider names, whether they appeared to belong to the same category of private vocational organisations, and whether any name implied higher prestige, stronger digital orientation or greater motivation than others. This objective ensured that the providers did not introduce unintended signalling effects and that their rotation across the three profiles avoided systematic associations with particular demographic groups. Within each experiment and sector, paraphrased variants of the email, application letter and CV bullet points were prepared. These variants rotated the wording of work tasks, interests and profile statements while preserving the underlying content. During the pre-tests, the alternative wording was distributed across participants so that each variant appeared in every demographic and AI-training condition. Questionnaire responses were then compared across variants to assess whether any particular formulation systematically increased perceived productivity, motivation or suitability.

The final set of materials used in the experiments comprised only those versions that passed the screening process, helping to ensure that all signals were clearly isolated and that other productivity-related information was balanced across applicants, apart from the intended AI-related digital-skills manipulation. The outcomes of the pre-test assessment were documented in the ethics submission, and the study subsequently received full ethical approval as a field experiment.

3.5 Application Sending

Between January and June 2025, the research team submitted applications for job vacancies twice per week. During this period, applications were submitted to 258 vacancies in the race experiment, 250 in the age experiment, 256 in the sexual-orientation experiment and 252 in the autism-spectrum-disclosure experiment. Three matched applications were submitted to each vacancy. Interview invitations and rejections were recorded by monitoring the applicants' email accounts and mobile phones. Firms communicated with applicants exclusively by email.

Three matched applications were submitted for each vacancy. This matched-applicant design strengthens internal validity by holding job-specific characteristics constant across treatment conditions, enabling within-vacancy comparisons that reduce unobserved heterogeneity in employer demand, job requirements and labour market conditions. All submissions occurred within one day of the advertisement appearing, and the order of submission was rotated to minimise ordering effects. One third of enquiries came first from the majority applicant without AI-related digital skills, one third from the underrepresented applicant without AI-related digital skills and one third from the underrepresented applicant with AI-related digital skills.

Submitting multiple applications to the same firm is central to the identification strategy because it holds constant employer-specific factors, job characteristics and recruitment conditions, allowing differences in responses to be attributed more directly to the experimental signals, with less influence from variation across firms or vacancies. Although matched designs improve statistical efficiency and causal inference, they may increase the risk of employer detection (Phillips, 2019). Several procedural safeguards were implemented to mitigate this possibility, namely variation in wording, staggered submission timing within the same day and rotation of the order of submission. No indication of detection or suspicion emerged during the study period, and no firms contacted applicants regarding similarities between submissions.

For research purposes, the team screened the webpages of organisations advertising job openings and documented whether they reported written equality, diversity and inclusion (EDI) policies, as well as their size in terms of employee numbers. Firm size was coded using publicly available information drawn from company websites, company registers and professional networking platforms. No firms were left unclassified for the firm-size variable. While such sources are widely used in correspondence studies, they may introduce measurement error due to incomplete reporting or variation in disclosure practices. To mitigate this issue, firm-size classifications were cross-checked across multiple sources where available. In total, 31.0 per cent of organisations reported written equality, diversity and inclusion policies, and 33.95 per cent were classified as large firms, defined as employing more than 250 staff. In addition, information on wage sorting was collected by recording the average gross annual wage whenever this was stated in the vacancy advertisement. This information was available in 63.3 per cent of cases. This procedure enabled an examination of whether underrepresented applicants, with or without AI-related digital skills, accessed occupations associated with lower wages, with potential implications for income gaps (Drydakis, 2009; Drydakis, 2025c).

4. Descriptive statistics

4.1 Interview invitations

Table 1 presents the interview invitation results from the experiments. Interview invitation rates and matched statistical comparisons are reported to assess whether signalling a productivity-related AI-related digital skill is associated with differences in interview-invitation outcomes. Because applications were submitted in matched sets within the same vacancy, interview outcomes are not independent across applicants. Statistical comparisons therefore use pairwise McNemar tests, which evaluate within-vacancy differences in binary outcomes between applicant groups and account for the matched structure of the experimental design. In addition, an omnibus Cochran's Q test is reported to assess whether interview invitation probabilities differ jointly across all three matched applicant conditions. Following the table notation, estimates with $p<0.10$ are described as statistically significant at the 10% level, while $p<0.05$ and $p<0.01$ denote statistical significance at the 5% and 1% levels, respectively.

Across Panels I–IV, majority applicants without AI-related digital skills receive more interview invitations than underrepresented applicants without such skills ($p<0.01$ in all experiments). Majority applicants without AI-related digital skills also receive more invitations than underrepresented applicants signalling AI-related digital skills ($p<0.01$ in all experiments). Comparisons between underrepresented applicants with and without the AI-related signal vary across experiments. The signal is associated with higher invitation rates in the sexual-orientation and autism-spectrum disclosure experiments ($p < 0.01$), a marginally significant increase in the age experiment ($p < 0.10$), and no statistically significant difference in the race experiment ($p > 0.10$).

[Table 1]

4.2 Wage sorting

Table 1 also presents the mean advertised wages for jobs in which applicants were invited to interview, using data from Experiments One to Four. Because advertised wages are fixed at the vacancy level and identical for all applicants within a matched set, any observed wage differences reflect variation across vacancies rather than differential salary offers to individual applicants. Wage-sorting outcomes therefore arise from differences in interview invitation rates across vacancies offering different posted wage levels. The analysis therefore examines whether applicants from different groups are more or less likely to receive interview invitations from higher-paying or lower-paying vacancies. In this context, wage sorting reflects selection into different segments of the wage distribution through employer screening decisions, as distinct from direct wage discrimination or wage negotiation.

Across Panels I–IV, underrepresented applicants without AI-related digital skills are invited to interviews for lower-paid vacancies than majority applicants without such skills, with statistically significant differences in all experiments (race: $p<0.05$; age, sexual orientation and autism-spectrum disclosure: $p<0.01$). When underrepresented applicants signal AI-related digital skills, mean advertised wages are higher in all four experiments, although differences relative to majority applicants without AI-related digital skills remain statistically significant (race, age and sexual orientation: $p<0.05$; autism-spectrum disclosure: $p<0.01$). Comparisons between underrepresented applicants with and without the signal do not reach statistical significance within individual experiments ($p>0.10$ in all panels).

5. Estimates

5.1 Interview invitations

Table 2, Models I–V, presents the results of probit regression models. The models report marginal effects, which show the estimated change in the probability of being invited to an interview relative to the relevant reference group. The reference category is majority applicants without AI-related digital skills. All models control for employer characteristics (i.e. sector, firm size and the presence of written EDI policies), as well as experimental controls (i.e. job application order and application type). Standard errors are clustered at the firm (job-opening) level to account for the matched-application design, in which multiple applications were submitted to the same employer.

Model I focuses on race. Black British women without AI-related digital skills were 10.2 percentage points less likely to be invited to an interview than White British women without AI-related digital skills ($p<0.01$). When Black British women signalled AI-related digital skills, their disadvantage decreased to 8.2 percentage points ($p<0.01$). The difference between the two coefficients is statistically insignificant (Wald test = 1.71, $p>0.10$). Although the coefficient is smaller in magnitude for Black British women signalling AI-related digital skills, the model does not provide statistical evidence that the AI-related signal reduces the racial interviews invitation gap in this specification.

Model II examines age-based differences. Older women without AI-related digital skills were 15.7 percentage points less likely to receive interview invitations than younger women without AI-related digital skills ($p<0.01$). For older women signalling AI-related digital skills, the disadvantage narrowed to 12.3 percentage points ($p<0.01$). The reduction is statistically significant (Wald test = 4.51, $p<0.05$). Model III examines sexual orientation. Lesbian women without AI-related digital skills were 13.5 percentage points less likely than heterosexual women without AI-related digital skills to receive interview invitations ($p<0.01$). Among lesbian women signalling AI-related digital skills, the gap decreased to 8.1 percentage points ($p<0.01$). The reduction is statistically significant (Wald test = 7.81, $p<0.01$). Model IV focuses on autism spectrum disclosure. Women disclosing autism spectrum status without AI-related digital skills were 16.2 percentage points less likely to be invited to interviews than women without autism spectrum disclosure and without AI-related digital skills ($p<0.01$). When women disclosing autism spectrum status signalled AI-related digital skills, the disadvantage decreased to 9.9 percentage points ($p<0.01$). The reduction is statistically significant (Wald test = 10.49, $p<0.01$).

Model V aggregates data across all four experiments. On average, underrepresented women without AI-related digital skills were 13.7 percentage points less likely to be invited to interviews than majority women without AI-related digital skills ($p<0.01$). For underrepresented women signalling AI-related digital skills, the disadvantage decreased to 9.7 percentage points ($p<0.01$), although it remained statistically significant. The difference between the two coefficients is statistically significant (Wald test = 20.22, $p<0.01$), indicating that while signalling AI-related digital skills is associated with a reduction in the interview gap, a statistically significant difference remains.

In Model VI, to assess whether pooling across demographic contexts masks heterogeneity, additional specifications include interaction terms between experimental conditions and an indicator for underrepresented women with AI-related digital skills, defined relative to majority women without such skills. The autism-spectrum disclosure experiment serves as the reference category, and the interaction terms evaluate whether the estimated association between this signalling condition and interview invitations differs in the race, age, and sexual-orientation experiments compared with the autism-spectrum disclosure condition. The interaction coefficients are small and statistically insignificant, suggesting that the estimated association is broadly similar across demographic contexts. These results support the interpretation of the pooled model while indicating that observed variation reflects contextual differences, with no evidence of fundamentally distinct effects across demographic groups.

[Table 2]

Moreover, in **Table 3**, Model I, interaction terms between occupational sectors and the condition indicating underrepresented women with AI-related digital skills are included to examine whether the association between this signalling condition and interview invitations varies across occupational contexts. Digital and Marketing Support is the reference sector. The main coefficient for underrepresented women with AI-related digital skills therefore refers to this sector, while the interaction terms indicate how the corresponding association differs across the other sectors. The interaction estimates suggest weaker estimated responses in several sectors relative to the reference category, although the strength of evidence varies across occupational contexts. Statistically significant differences are observed in retail sales and customer service and finance and payment processing at the 1% level, and in hospitality and front-of-house and stock and inventory control at the 5% level. Facilities and logistics support is marginally significant at the 10% level. Differences in construction and trades support, education and youth programme support, transport, delivery and dispatch, and administrative support are not statistically distinguishable from the reference sector. These sectoral differences should be interpreted cautiously. **Supplementary Table S2** indicates that AI-related applications can be identified across all occupational sectors included in the study, so the results should not be read as evidence that AI-related digital skills are relevant in some sectors but irrelevant in others. A more limited interpretation is that employers may vary in how they read, prioritise or reward the same AI-related digital skills signal across occupational settings. This variation may reflect differences in perceived task fit, employer familiarity with AI-enabled tools, the salience of digital credentials in screening, or sector-specific recruitment conventions.

[Table 3]

5.2 Sensitivity Analysis and the Heckman–Siegelman Critique

The Heckman–Siegelman critique highlights an important identification concern in correspondence designs, as differences in interview-invitation rates may reflect not only differences in mean employer evaluations but also group differences in the variance of unobserved productivity or in the perceived precision of applicant signals (Heckman and Siegelman, 1993). If employers make interview invitation decisions by comparing latent perceived productivity with a hiring threshold, group differences in dispersion can affect the probability that otherwise standardised applicants cross that threshold. Under such conditions, an observed interview invitation gap may partly reflect distributional features of the applicant signal, not only differential treatment in mean evaluations. This issue is considered here as a sensitivity concern, not as a basis for adjudicating among taste-based discrimination, statistical discrimination or other screening mechanisms.

Table 3, Model II provides an initial diagnostic by examining whether interview invitation gaps vary across observable organisational contexts where uncertainty or informality might plausibly be more salient. The model introduces interaction effects between the applicant-group conditions and firm-level characteristics, specifically firm size and the presence of written equality, diversity and inclusion policies. If dispersion in perceived productivity or signal precision were especially relevant in smaller or less formalised firms, one might expect larger gaps in those settings, or stronger changes in the AI-related digital skills association where the signal provides additional information about applicant productivity. The results do not show statistically significant variation across these organisational proxies. The relevant interaction coefficients are small and statistically insignificant, and robustness checks using alternative firm-size thresholds produce substantively similar conclusions. This evidence does not indicate that the observed interview invitation gaps are systematically concentrated in settings where Heckman–Siegelman-type concerns might be expected to be stronger. However, these interactions are indirect tests. Firm size and public EDI policies are imperfect proxies for employer uncertainty, recruitment formality and signal precision, so the results should not be read as ruling out the Heckman–Siegelman critique or as supporting one discrimination mechanism over another.

The study's design does not permit the implementation of the Neumark (2012) decomposition. Neumark's approach relies on independent variation in observable productivity signals, which can be used to distinguish mean differences from differences in signal variance or precision across groups. In the present experiments, applicant qualifications are intentionally standardised to maintain comparability across profiles. The AI-related digital skills signal is itself the experimental treatment, not a graded or independently varied measure of signal precision. The design therefore does not provide the independent precision variation required for the Neumark decomposition.

To explore the issue further, **Table 4** reports heteroskedastic probit estimates in which the probability of receiving an interview is modelled as a function of underrepresented status, AI-related digital skills signalling and the full set of controls, while the residual standard deviation is allowed to vary by applicant group. The estimated lnsigma parameters for underrepresented applicants without AI-related digital skills and with AI-related digital skills are −1.476 ($p<0.01$) and −1.095 ($p<0.05$), respectively. A Wald test rejects the joint null hypothesis that these coefficients are equal to zero ($\chi^2(2)=13.52$, $p<0.01$). Under the model's parameterisation, these negative estimates imply lower estimated residual dispersion for underrepresented applicants relative to the baseline group of majority women without the AI-related digital skills signal.

This finding should be interpreted cautiously, particularly because interview invitation rates are below 50 per cent. In a threshold model, low interview invitation rates suggest that the relevant cutoff lies in the upper part of the latent evaluation distribution. If the standardised applicant profile lies below that threshold, lower dispersion among underrepresented applicants may itself reduce the probability of crossing the cutoff, even when mean perceived productivity is the same. The lnsigma estimates therefore do not provide a directional test that can determine whether the baseline interview invitation gap reflects discrimination, variance-related mechanisms or a combination of both. The cross-group variance contrast in the heteroskedastic probit is identified through the model's distributional and functional-form assumptions, not through independent experimental variation in signal precision. The estimates should therefore not be interpreted as direct measures of employer beliefs about perceived productivity dispersion. They are better understood as a sensitivity exercise that examines whether allowing residual dispersion to differ across applicant groups qualifies the interpretation of the interview invitation patterns. The overall evidence does not show that observed gaps are concentrated in firm contexts where uncertainty-based screening would be expected to be stronger. Nor does it provide experimental evidence that decisively adjudicates the Heckman–Siegelman critique. More broadly, the results should not be read as distinguishing taste-based discrimination from statistical discrimination or other forms of employer screening. The baseline interview invitation gap and the uplift in interview invitations due to AI-related digital skills remain the central causal comparisons identified by the design. The variance-based analyses are supplementary diagnostics, and their interpretation depends on threshold assumptions, distributional assumptions and the absence of independent variation in signal precision.

[Table 4]

5.3 Wage sorting

Table 5 presents results from five Ordinary Least Squares (OLS) regression models estimating the natural logarithm of hourly wages for vacancies in which applicants were invited to interview. The coefficients can be interpreted approximately as percentage differences in hourly wages relative to the relevant reference group. The reference category comprises majority applicants without AI-related digital skills. All models control for employer characteristics and experimental controls, and standard errors are clustered at the firm level.

In Model I, Black British women without AI-related digital skills are associated with interview invitations from jobs offering hourly wages approximately 4.3 per cent lower than those associated with White British women without AI-related digital skills ($p<0.05$). Among Black British women signalling AI-related digital skills, the estimated difference is smaller, at approximately 2.0 per cent ($p<0.10$). The difference between the two coefficients is statistically significant at the 10% level (Wald test=3.00, $p<0.10$). These results indicate wage sorting associated with race, with AI-related digital skills signalling related to a modest reduction in the wage-sorting gap, although the difference is not eliminated.

Model II shows that older women without AI-related digital skills are associated with interview invitations from jobs offering wages approximately 3.4 per cent lower than those associated with younger women without AI-related digital skills ($p<0.05$). Among older women signalling AI-related digital skills, the estimated difference declines to approximately 0.9 per cent and is not statistically significant ($p>0.10$). The difference between the two coefficients is statistically significant at the 10% level (Wald test=3.34, $p<0.10$). In Model III, lesbian women without AI-related digital skills are associated with interview invitations from jobs offering wages approximately 5.1 per cent lower than those associated with heterosexual women without AI-related digital skills ($p<0.01$). Among lesbian women signalling AI-related digital skills, the difference decreases to approximately 3.1 per cent ($p<0.05$). The difference between the two coefficients is statistically significant at the 10% level (Wald test=2.99, $p<0.10$).

Model IV indicates that women disclosing autism spectrum status without AI-related digital skills are associated with interview invitations from jobs offering wages approximately 6.4 per cent lower than those associated with women not disclosing autism spectrum status and not signalling AI-related digital skills ($p<0.01$). Among women disclosing autism spectrum status and signalling AI-related digital skills, the difference narrows to approximately 4.5 per cent ($p<0.01$). The difference between the two coefficients is statistically significant at the 10% level (Wald test=3.05, $p<0.10$).

Model V pools the data across the four experiments and shows that underrepresented women without AI-related digital skills are associated with interview invitations from jobs offering wages approximately 6.8 per cent lower than those associated with majority women without AI-related digital skills ($p<0.01$). Among underrepresented women signalling AI-related digital skills, the difference decreases to approximately 4.1 per cent ($p<0.01$), although it remains statistically significant. The difference between the two coefficients is statistically significant at the 1% level (Wald test=8.01, $p<0.01$). These results indicate that signalling AI-related digital skills is associated with smaller wage-sorting differences, although the gap is not eliminated**.**

[Table 5]

6. Discussion

6.1 Outcomes evaluation

The experiment reveals a clear shortlisting disadvantage for women whose applications signal underrepresented status. Applicants identified by race, age, sexual orientation or autism-spectrum disclosure receive fewer invitations than otherwise equivalent majority-group women. Since qualifications and application quality are held constant, these differences indicate unequal employer responses at the screening stage. The results should not, however, be interpreted as evidence favouring a taste-based explanation over statistical discrimination. The design identifies differences in employer responses, but it does not reveal whether those responses arise from prejudicial preferences, uncertainty about productivity or other forms of recruitment filtering.

The AI-related digital skills signal improves outcomes for underrepresented women in the pooled analysis, but only partially, as a statistically significant disadvantage remains relative to majority-group women without the signal. Underrepresented applicants who present this credential receive more favourable responses than comparable applicants without the credential, indicating that employers attach value to the signal. The main empirical result is therefore an AI-related interview invitation gain for underrepresented applicants, while the persistence of disadvantage limits any inference that discrimination itself has diminished. The majority-group applicant without the AI signal provides a useful benchmark for assessing whether underrepresented applicants move closer to majority-group outcomes, although it cannot show whether the AI signal carries the same return for majority-group applicants. In the labour-market segment studied here, formal AI-related credentials are not assumed to be universal among comparable applicants. The relevant comparison is therefore whether underrepresented applicants who acquire such a credential move closer to the majority-group comparator they may commonly face in entry-level recruitment. Viewed through the AI Capital framework (Drydakis, 2024), this pattern is consistent with the proposition that AI-related skills, as a component of AI Capital, can generate labour-market returns when they are made visible to employers. In this experiment, however, the evidence concerns the return to signalling AI-related digital skills at the shortlisting stage and does not identify the productive effect of AI Capital itself (Drydakis, 2025a;b; 2026).

The size of the improvement is also informative. AI-related digital skills help, but their effect is not large enough to equalise outcomes. This may reflect how such skills are understood in the vacancies studied. In mid-level roles, AI-enabled tools may be relevant to administrative routines, customer interaction or workflow support, but they may not yet define the core occupational profile. Employers may therefore value the signal as evidence of familiarity with AI-enabled tools, general digital preparedness, initiative or technological adaptability, while still giving considerable weight to other screening criteria. Several mechanisms could account for the observed uplift[1]. Employers may use the credential to update beliefs about applicants' productivity, read it as evidence of readiness for technology-mediated work or treat it as offsetting part of a group-based penalty without changing the source of that penalty. These explanations are empirically compatible with the results. From an AI Capital perspective, the observed uplift therefore suggests that employers attach labour-market value to a visible signal of AI-related skills, although the experiment cannot determine precisely which employer belief or screening mechanism produces that return. The discussion therefore uses taste-based discrimination, statistical discrimination and signalling theory as interpretive lenses, without claiming to distinguish decisively among them.

The wage-related results point in the same direction. Interview access is only one dimension of the recruitment process. Underrepresented women not only receive fewer interview

[1] For context, the pooled descriptive results in Table 1, Panel V imply a 3.1 percentage-point increase in interview invitations associated with the AI-related digital-skills signal, while the pooled probit estimates in Table 2, Model V imply an adjusted increase of approximately 4 percentage points. There is currently no established like-for-like benchmark for the expected interview-invitation return to a six-month AI-related digital-skills training programme among non-graduate applicants. The observed uplift is therefore interpreted as economically meaningful but modest, without reference to a precisely defined expected effect size.

opportunities, but the positive responses they receive are also associated with lower-paid vacancies. This suggests that unequal outcomes are reflected not only in a reduction in the volume of interview opportunities, but also in the quality of those opportunities, as captured by the wage level attached to the vacancies generating positive employer responses.

The Heckman–Siegelman critique also places limits on interpretation. The heteroskedastic probit estimates indicate lower residual dispersion for underrepresented women than for the baseline group, but this pattern does not resolve the variance-based question. When interview invitation probabilities are low, the effect of group-specific dispersion may depend on where the hiring threshold lies in the latent evaluation distribution. Under some threshold configurations, lower dispersion may itself reduce interview invitations. Since the experiment does not introduce independent variation in the precision or informativeness of applicant signals, the variance analysis should be read as a model-based sensitivity check. It cannot rule out Heckman–Siegelman-type artefacts or distinguish taste-based discrimination from statistical discrimination and other forms of employer screening.

6.2 AI Capital, inequality and the conversion of skills into opportunity

The findings extend the AI Capital framework by introducing a distributional dimension to the relationship between AI-related capabilities and labour-market outcomes. Existing work conceptualises AI Capital as AI-related knowledge, skills and capabilities that can generate returns through employment, earnings, productivity and innovation (Drydakis, 2024, 2025a, 2025b, 2026). For underrepresented groups, however, the relevant question is not only whether such capabilities have economic value, but also whether that value can be converted into labour-market opportunity when demographic disadvantage persists. This distinction suggests four analytically distinct processes through which AI Capital may generate economic returns, namely formation, signalling, employer valuation and conversion (Cai and Tomlinson, 2023). Formation concerns the acquisition of AI-related capabilities. Signalling concerns their visibility to employers. Valuation concerns the value employers attach to those signals, while conversion concerns whether that value translates into employment opportunities. These processes need not be sequential or equally effective. The present experiment is particularly informative about signalling and about the extent to which a visible AI-related credential is valued and converted into shortlisting opportunities. In the pooled analysis, employers respond positively to the AI-related digital-skills signal, yet the remaining disadvantage relative to the majority-group comparator shows that a valued signal does not necessarily translate into parity of outcomes.

The experimental design makes this distinction empirically visible by separating the baseline penalty associated with underrepresentation status from the return to signalling AI-related digital skills among underrepresented applicants. In the pooled analysis, underrepresented women without the AI-related digital-skills signal were 13.7 percentage points less likely to receive an interview invitation than otherwise comparable majority-group women. Among underrepresented women who signalled AI-related digital skills, the corresponding disadvantage was 9.7 percentage points. The statistically significant 4-percentage-point difference identifies the interview-invitation return associated with the AI-related digital-skills signal among underrepresented applicants. The signal offsets approximately 29 per cent of the baseline interview-invitation penalty, while a substantial and statistically significant disadvantage remains. The results therefore show that a positive return to signalling AI-related capabilities and persistent demographic disadvantage can operate simultaneously.

This empirical separation broadens the analytical usefulness of AI Capital for research on inequality. It distinguishes inequalities in the formation and distribution of AI-related capabilities from inequalities in the extent to which those capabilities are rewarded and converted into opportunity. Possessing technologically relevant skills is therefore not equivalent to realising their full labour-market return. Policies may widen access to AI-related education and training while inequalities persist at subsequent stages of employer evaluation and recruitment. The effectiveness of AI-related skills policy for underrepresented groups should consequently be assessed not only by participation or competence acquisition, but also by whether those investments ultimately generate improvements in employment access, earnings and career progression. From this perspective, barriers to the valuation and conversion of AI Capital are as important as inequalities in its initial formation.

This extension should nevertheless be interpreted within the limits of the experimental design. The analysis identifies the baseline employer-response penalty associated with underrepresentation status and the return to AI-related digital-skills signalling among underrepresented applicants, but it does not establish that the signal causally reduces discrimination or distinguish among taste-based, statistical, variance-based or other screening mechanisms. Nor, without a majority-group applicant carrying the same AI-related digital-skills signal, can the study determine whether majority and underrepresented applicants receive different causal returns to that signal. The theoretical contribution is therefore more specific. Signalling AI-related capabilities can generate labour-market value at the shortlisting stage, but the conversion of that value into opportunity may remain constrained by the labour-market conditions facing particular groups. Extending the AI Capital framework in this way allows it to address not only adaptation to AI-driven economic change, but also the distribution of the opportunities generated by that transition. The same underlying argument also applies to wage sorting, where AI-related digital-skills signalling is associated with more favourable access to higher-paid interview opportunities, although disadvantage remains.

6.3 Consequences for Firms and Society

The broader implication of this study is that digital upskilling may improve the recruitment prospects of underrepresented applicants, but it cannot carry the burden of inclusion alone. A valued credential may alter employer responses, yet persistent differences after the signal is introduced show that sorting mechanisms still matter. Policies focused on AI-related training therefore need to be paired with clearer shortlisting criteria, systematic monitoring of hiring outcomes, accountability for unequal outcomes, and stronger enforcement of anti-discrimination standards. As AI-related digital skills become more prominent in employment, the distribution of those skills is only one issue. How employers read, rank, and reward them across applicant groups is equally important.

The outcomes documented in this study have implications at the individual, organisational and societal levels. For underrepresented individuals, lower interview-invitation rates and greater exposure to lower-paid opportunities may constrain economic mobility and career development (Kaur, 2024; Brynin and Güveli, 2012). Reduced access to interviews can lengthen job-search processes, delay entry into stable employment and limit opportunities to accumulate relevant experience, with consequences for longer-term earnings trajectories. Although signalling AI-related digital skills improves outcomes for underrepresented applicants, the persistence of disadvantage indicates that additional credentials remain insufficient to eliminate unequal outcomes at the shortlisting stage. This may weaken confidence in upskilling as a sufficient route to labour-market inclusion, particularly where applicants perceive that valued skills improve their prospects while recruitment barriers continue to constrain equal access to opportunities. Labour-market barriers may also be associated with psychological effects, such as reduced confidence and job-search fatigue (Smethurst et al., 2024; Bierbaum and Nillesen, 2021). For women specifically, these patterns matter because they may intersect with existing gender inequalities in pay, occupational sorting and career progression as digital competencies become more relevant across occupations.

For firms, the findings suggest that unequal recruitment outcomes may be associated with inefficient talent allocation. When applicants with comparable observable qualifications receive different shortlisting outcomes, employers may overlook candidates whose skills could support organisational adaptability and digital transformation (Drydakis, 2024). This matters especially where AI-related competencies are increasingly relevant to administrative routines and sector-specific digital systems. The study cannot determine whether firms value the AI-related digital skills signal differently for underrepresented and majority applicants, because the design does not include a majority-group applicant with the same signal. The implication for organisations is therefore more specific, as persistent disadvantage among applicants with relevant credentials may prevent firms from fully utilising available talent. It also points to the need for closer scrutiny of how shortlisting criteria are applied across applicants with comparable observable qualifications.

At the societal level, the results indicate that technological transition does not automatically remove barriers in recruitment (Niavis et al., 2025; Valiati and Möller, 2025). AI-related digital skills improve interview invitation outcomes for underrepresented women in the experiment, but remaining disparities suggest that skills policy alone is unlikely to deliver equal access to employment opportunities. If such barriers persist, inequalities in income, occupational mobility and wealth accumulation may continue over time. This has implications for productivity and social cohesion, since inconsistent evaluation of comparable applicants may result in the underutilisation of available skills. In the context of rapid AI-driven transformation, the findings suggest that digital education strategies may need to be linked with measures addressing recruitment practices and the evaluation of applicant signals. The findings also point to interconnected policy implications for individuals, organisations, education providers and government. At the individual level, underrepresented applicants may benefit from combining upskilling with strategies that increase access to inclusive employers, mentoring relationships and professional networks that can help them navigate recruitment barriers. Greater awareness of the limits of training alone may also support more informed decisions about course selection, career pathways and employer targeting.

Within organisations, the findings support closer scrutiny of recruitment processes. Reviewing shortlisting data, clarifying evaluation criteria, strengthening equality, diversity and inclusion frameworks and using structured assessment procedures may help reduce inconsistency in how qualifications and applicant profiles are assessed (Kyriakidou et al., 2025; Cramarenco et al., 2023; Pagani et al., 2023; Georgieff and Hyee, 2022). The null findings for written equality, diversity and inclusion policy interactions in Table 3, Model II, should not be read as evidence that such frameworks are ineffective. They are better interpreted as a reminder that publicly stated commitments may not translate automatically into consistent shortlisting practice. A written policy can signal organisational intent, but its practical effect may depend on recruiter training and clear evaluation criteria. The persistence of disadvantage relative to the observed majority no-AI comparator also underlines the need to examine whether recruitment decisions are applied consistently across demographic groups. As organisations increasingly adopt AI-enabled recruitment tools, effective oversight is needed to ensure that automated systems avoid reproducing biases already present in human decision-making (Chen, 2023).

For educators and training providers, the findings highlight the importance of designing AI-related digital skills programmes that are accessible, credible and closely aligned with labour-market requirements (Chizoba and Chinda, 2025). This implication is particularly relevant in the context of the 2026 Skills England agenda, which places greater emphasis on classifying occupational skills, digital literacy and AI-related capabilities within a national skills framework (Skills England, 2026). AI-related training should therefore be designed not only as generic digital provision, but as a route through which underrepresented applicants can build visible AI Capital that employers recognise during recruitment (Drydakis, 2024). Flexible provision for learners facing structural barriers, targeted outreach to underrepresented groups and collaboration with employers may strengthen the visibility and recognition of training during shortlisting. Greater clarity and standardisation in AI-related qualifications may also support employer interpretation, particularly where emerging forms of training vary in format, duration or certification (Bone et al., 2025).

At the public policy level, the evidence suggests that digital-skills strategies should be embedded within broader labour-market equality frameworks. Publicly funded training may improve applicants' prospects, but persistent disadvantage relative to the observed majority no-AI comparator points to the continued importance of anti-discrimination enforcement, transparent shortlisting criteria and monitoring of recruitment outcomes (D'Ancona and Valles Martinez, 2021; Rafferty, 2020; Valfort, 2018). Because early-stage hiring decisions often involve subjective judgement, policymakers may consider encouraging structured evaluation procedures and routine analysis of interview invitation patterns. Designing AI-skills initiatives with explicit attention to inclusion may help ensure that the emerging skills system expands access to occupations without leaving unequal recruitment practices unaddressed.

6.4 Study's contribution

This study contributes field-experimental evidence on employer responses to a contemporary digital productivity signal framed around AI-related digital skills. By embedding this signal within a correspondence design, the analysis shows how established experimental methods can be adapted to examine recruitment responses to emerging technological credentials. This matters because much of the existing debate on AI and labour-market inequality focuses on algorithmic screening or automation, while less attention has been paid to how employers evaluate applicants who present AI-related digital skills as part of their own profile. The empirical contribution is centred on two identified comparisons. First, the design estimates the interview invitation disadvantage associated with the underrepresentation signal among applicants without an AI-related digital skills signal. Second, it estimates the interview invitation gain associated with the AI-related digital skills signal among underrepresented women. These comparisons provide causal evidence on baseline shortlisting disadvantage and on the value of AI-related digital skills signalling for underrepresented applicants in early-stage recruitment. The study also contributes to the correspondence-testing literature by examining several underrepresentation signals within a common experimental structure. Race, age, sexual orientation and autism-spectrum disclosure are analysed separately, while application quality, qualifications and job-seeking context are standardised. This allows the study to document whether similar shortlisting patterns appear across different identity dimensions and whether an AI-related digital skills signal improves responses within each experimental setting. Understanding how identity shapes employment outcomes in causal terms is important for policy making.

A further contribution lies in connecting correspondence evidence with the AI Capital framework. This connection is important for the economics of AI because the AI Capital framework is concerned with how AI-related resources are acquired, signalled and converted into employment and business outcomes (Drydakis, 2024; 2026). This process is especially important for underrepresented groups, whose access to labour-market opportunities may be shaped both by emerging technological requirements and by persistent recruitment barriers. The study therefore clarifies both the value and the limits of AI Capital in recruitment. It also contributes to debates on digital upskilling, skills policy and innovation policy in business (Drydakis, 2026). In the context of Skills England's emerging skills infrastructure, the study provides experimental evidence on whether an AI-related credential is recognised in real recruitment decisions (Skills England, 2026).

6.5 Limitations and future research

The study's limitations should be considered when interpreting the findings. The experiments were conducted in London in 2025 and focused on online vacancies across ten occupational sectors, restricted to private-sector, full-time roles not requiring a university degree. All fictitious applicants were women with non-university profiles. This setting captures a substantial and policy-relevant segment of the labour market, but it does not cover public-sector recruitment, informal hiring channels, graduate occupations, male applicants or non-binary applicants. London is also a distinctive labour-market context, where employer practices, applicant pools and expectations around digital skills may differ from those in other regions. The findings should therefore be read as evidence from a specific institutional and occupational setting, with future research needed across regions, sectors, qualification levels and national contexts.

Statistical sensitivity also requires attention. Each experiment included approximately 250 matched vacancies, which provides scope to detect meaningful differences in interview-invitation probabilities but less precision for smaller effects within each demographic category. The pooled analysis increases statistical power and helps identify broader patterns, yet larger samples would allow more detailed assessment of variation across identity groups, occupations and employer characteristics. Similar patterns across experiments should not be read as evidence that the same underlying mechanism operates in each case. The AI-related digital skills signal is another important boundary condition. The signal was operationalised through a six-month certificate combining exposure to AI tools and sector-specific applications. This is a realistic credential, but it captures only one type and level of training. It does not vary course duration or distinguish between foundational and advanced AI competence. Because the comparison applicants hold nondigital certifications, the design can identify whether employers respond to an AI-related digital-skills credential as a broader digital productivity signal relative to a nondigital credential. However, it cannot determine whether this response reflects AI-related competence specifically or broader digital literacy, adaptability or technological confidence. Employers may therefore have interpreted the credential as signalling wider digital competence in addition to, or instead of, AI-specific skills. Future correspondence studies could include separate AI-related, general digital-skills and nondigital certification conditions to distinguish more precisely how employers value AI-specific competence relative to broader digital literacy and other forms of human capital.

The absence of a majority-group applicant with the AI-related digital skills signal is a limitation. A full factorial design comprising majority-group applicants with and without the signal, alongside underrepresented applicants with and without the signal, would allow researchers to estimate whether the return to AI-related digital skills differs across groups. A related limitation concerns mechanism. The study can identify differences in employer responses, but it cannot determine whether these arise from taste-based discrimination, statistical discrimination, variance-based screening or other forms of recruitment filtering. The theoretical frameworks are therefore used to interpret the findings, not to adjudicate decisively among alternative explanations. Methodological constraints inherent in correspondence testing also apply. The study observes employer responses at the initial screening stage, focusing on interview invitations and wage-related sorting, not job offers, negotiated pay, workplace treatment or career progression. Written applications cannot capture all features of recruitment, particularly interpersonal interaction or post-hire evaluation. Future research could combine correspondence tests with employer surveys and laboratory experiments to examine whether early-stage patterns persist across later stages of hiring.

The use of explicit disclosure signals also requires caution. Sexual orientation and autism-spectrum status were indicated through application materials, consistent with correspondence-testing conventions, but real applicants may disclose these characteristics in varied ways or not disclose them at all. The findings therefore capture employer responses to disclosed identities, not the full experience of all individuals within these groups. The study also examines four dimensions of underrepresentation separately. This improves clarity but does not capture more complex intersectional profiles. Future experiments could vary combined identity signals to examine how AI-related credentials are interpreted when applicants occupy multiple marginalised positions.

The matched-application design strengthens internal validity by holding vacancy and employer conditions constant, but it may also shape employer behaviour if similar applications are evaluated jointly. No direct evidence of detection was observed. If employers became aware of similarities between applications, estimated differences may understate or otherwise alter the measured effects. Future studies may consider alternative sampling or randomisation strategies to reduce this risk further. Organisational information is also limited. The study includes indicators such as firm size and the public presence of equality, diversity and inclusion policies, but these measures provide limited insight into how recruitment decisions are made internally. Public EDI statements may not correspond to substantive practice, and their absence does not necessarily indicate opposition to inclusion. The analysis therefore cannot establish whether organisational culture or recruiter training shape responses to AI-related credentials. Mixed-methods research linking correspondence evidence with organisational data could provide richer insight into how employers interpret emerging digital qualifications. The temporal context also matters. Employer familiarity with AI-related digital skills is likely to evolve as AI tools diffuse across occupations and training credentials become more common. A signal that is distinctive in 2025 may become routine in later recruitment cycles, changing its perceived value. Repeated correspondence experiments would be useful for assessing whether the observed patterns reflect an early phase of technological adjustment or more durable inequalities in how new skills are recognised.

7. Conclusions

This study provided field-experimental evidence on how employers responded to women who differed by underrepresentation status and by whether they signalled AI-related digital skills. Women from underrepresented groups received fewer interview invitations and were more likely to receive positive responses from lower-paid vacancies than otherwise comparable majority-group women. These patterns appeared across race, age, sexual orientation and autism-spectrum disclosure, indicating that disadvantage remained visible even when applicants had equivalent observable qualifications. AI-related digital skills were associated with improved interview invitation outcomes for underrepresented women in the pooled analysis. Applicants carrying this credential received more favourable responses than otherwise comparable underrepresented applicants without it, and their outcomes moved closer to those of the majority-group applicant without the credential. However, even with the AI signal, underrepresented women continued to experience disadvantage compared with majority-group women. The study therefore contributed evidence on the labour-market value of AI-related digital skills as an observable productivity signal for underrepresented women in early-stage recruitment. Viewed through the AI Capital framework, these findings suggest that signalling AI-related knowledge, skills and capabilities can generate labour-market returns at the recruitment stage. At the same time, the persistence of disadvantage indicates that the returns to AI Capital are shaped by the wider recruitment environment and that signalling such capital alone is insufficient to overcome existing barriers.

This improvement required careful interpretation. Because the experiment did not include a majority-group applicant with the same credential, it could not estimate whether the AI-related digital skills signal carried different returns across applicant groups. Nor could it establish that the observed reduction in the interview-invitation gap reflected a causal reduction in discrimination. The observed gain was compatible with a signalling interpretation, in which visible indicators of digital competence were valued during recruitment. However, the design did not identify a single behavioural mechanism. The gain may have reflected a general productivity signal, reduced uncertainty about applicants' productivity, demand for technologically adaptable workers or the capacity of a valued credential to offset part of a group-based penalty. The conclusions therefore focused on employer responses observed in the experiment, without assigning priority to one theory of discrimination. The policy message was consequently balanced. AI-related upskilling may help underrepresented applicants improve their position in recruitment, but it should not be treated as a substitute for institutional reform. Persistent disadvantage after the credential was introduced pointed to the need for more transparent shortlisting procedures, consistent evaluation of qualifications, stronger monitoring of recruitment practice and effective anti-discrimination enforcement. As AI-related digital skills become more visible in labour markets, inclusion strategies need to consider not only who acquires such skills, but also how employers interpret them across different applicant groups.

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Table 1. Interview Invitations and Advertised Wage Sorting by Applicant Group

Panel I. Experiment One. Race						
	White women without AI-related digital skills	**Black women without AI-related digital skills**	**Black women with AI-related digital skills**	**White women without AI-related digital skills vs Black women without AI-related digital skills**	**White women without AI-related digital skills vs Black women with AI-related digital skills**	**Black women without AI-related digital skills vs Black women with AI-related digital skills**
Job openings Invited to interviews Cochran's χ^2 (^)	258 63 (24.4%) 26.81; p<0.01***	258 39 (15.1%)	258 43 (16.6%)	McNemar's χ^2 (^^) 19.20; p<0.01***	McNemar's χ^2 (^^) 11.76; p<0.01***	McNemar's χ^2 (^^) 1.60; p>0.10
Wage sorting (£)	37,343.7 [2,401.2] N=32	35,422.7 [3,380.1] N=22	36,028.0 [2,183.3] N=25	t-test (^^) 2.44; p<0.05**	t-test (^^) 2.13; p<0.05**	t-test (^^) 0.73; p>0.10
Panel II. Experiment Two. Age						
	Younger women without AI-related digital skills	**Older women without AI-related digital skills**	**Older women with AI-related digital skills**	**Younger women without AI-related digital skills vs Older women without AI-related digital skills**	**Younger women without AI-related digital skills vs Older women with AI-related digital skills**	**Older women without AI-related digital skills vs Older women with AI-related digital skills**
Job openings Invited to interviews Cochran's χ^2 (^)	250 64 (25.6%) 53.69; p<0.01***	250 24 (9.6%)	250 30 (12.0%)	McNemar's χ^2 (^^) 36.36; p<0.01***	McNemar's χ^2 (^^) 23.12; p<0.01***	McNemar's χ^2 (^^) 3.60; p<0.10*
Wage sorting (£)	37,129.7 [3,093.6] N=37	34,206.6 [3,206.3] N=15	35,205.2 [1,682.4] N=19	t-test (^^) 3.05; p<0.01***	t-test (^^) 2.51; p<0.05**	t-test (^^) 1.71; p>0.10
Panel III. Experiment Three. Sexual orientation						
	Heterosexual women without AI-related digital skills	**Lesbian women without AI-related digital skills**	**Lesbian women with AI-related digital skills**	**Heterosexual women without AI-related digital skills vs Lesbian women without AI-related digital skills**	**Heterosexual women without AI-related digital skills vs Lesbian women with AI-related digital skills**	**Lesbian women without AI-related digital skills vs Lesbian women with AI-related digital skills**
Job openings Invited to interviews Cochran's χ^2 (^)	256 67 (26.1%) 30.75; p<0.01***	256 33 (12.8%)	256 45 (17.5%)	McNemar's χ^2 (^^) 27.52; p<0.01***	McNemar's χ^2 (^^) 8.96; p<0.01***	McNemar's χ^2 (^^) 7.20; p<0.01***
Wage sorting (£)	37,497.5 [2,023.2] N=44	35,116.5 [3,496.1] N=23	36,293.3 [2,042.1] N=30	t-test (^^) 3.53; p<0.01***	t-test (^^) 2.50; p<0.05**	t-test (^^) 1.53; p>0.10
Panel IV. Experiment Four. Autism-spectrum disclosure						
	Women without autism spectrum disclosure and without AI-related digital skills	**Women with autism spectrum disclosure and without AI-related digital skills**	**Women with autism spectrum disclosure and with AI-related digital skills**	**Women without autism spectrum disclosure and without AI-related digital skills vs Women with autism spectrum disclosure and without AI-related digital skills**	**Women without autism spectrum disclosure and without AI-related digital skills vs Women with autism spectrum disclosure and with AI-related digital skills**	**Women with autism spectrum disclosure and without AI-related digital skills vs Women with autism spectrum disclosure and with AI-related digital skills**
Job openings Invited to interviews Cochran's χ^2 (^)	252 60 (23.8%) 51.49; p<0.01***	252 17 (6.7%)	252 27 (10.7%)	McNemar's χ^2 (^^) 39.34; p<0.01***	McNemar's χ^2 (^^) 19.11; p<0.01***	McNemar's χ^2 (^^) 7.14; p<0.01***
Wage sorting (£)	38,303.5 [2,348.4] N=42	34,925.0 [3,096.1] N=14	35,735.7 [1,469.4] N=21	t-test (^^) 4.29; p<0.01***	t-test (^^) 4.57; p<0.01***	t-test (^^) 1.04; p>0.10
Panel V. Aggregated Outcomes across Experiments One-Four						
	Majority women without AI-related digital skills	**Underrepresented women without AI-related digital skills**	**Underrepresented women with AI-related digital skills**	**Majority women without AI-related digital skills vs Underrepresented women without AI-related digital skills**	**Majority women without AI-related digital skills vs Underrepresented women with AI-related digital skills**	**Underrepresented women without AI-related digital skills vs Underrepresented women with AI-related digital skills**
Job openings Invited to interviews Cochran's χ^2 (^)	1,016 254 (25.0%) 159.15; p<0.01***	1,016 113 (11.1%)	1,016 145 (14.2%)	McNemar's χ^2 (^^) 121.97; p<0.01***	McNemar's χ^2 (^^) 60.93; p<0.01***	McNemar's χ^2 (^^) 18.96; p<0.01***
Wage sorting (£)	37,596.3 [2,492.8] N=155	34,986.8 [3,292] N=74	35,883.8 [1,903.8] N=95	t-test (^^) 6.65; p<0.01***	t-test (^^) 5.76; p<0.01***	t-test (^^) 2.23; p<0.05**

Notes. Wage-sorting figures refer to advertised wages for vacancies in which applicants were invited to interview; wages are fixed at vacancy level and do not represent applicant-specific wage offers. Percentages are shown in parentheses. Standard deviations are shown in brackets. (^) Overall test across three groups. (^^) Pairwise test. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 2. Probit Job Invitation Estimates (Marginal Effects)						
	Model I: Race	**Model II: Age**	**Model III: Sexual orientation**	**Model IV: Autism-spectrum disclosure**	**Model V: Total**	**Model VI: Total**
Black women without AI-related digital skills ^	-0.102 (0.020)***	-	-	-	-	-
Black women with AI-related digital skills ^	-0.082 (0.021)***	-	-	-	-	-
Older women without AI-related digital skills ^^	-	-0.157 (0.021)***	-	-	-	-
Older women with AI-related digital skills ^^	-	-0.123 (0.023)***	-	-	-	-
Lesbian women without AI-related digital skills ^^^	-	-	-0.135 (0.022)***	-	-	-
Lesbian women with AI-related digital skills ^^^	-	-	-0.081 (0.024)***	-	-	-
Women with autism spectrum disclosure and without AI-related digital skills #	-	-	-	-0.162 (0.021)***	-	-
Women with autism spectrum disclosure and with AI-related digital skills #	-	-	-	-0.099 (0.022)***	-	-
Underrepresented women without AI-related digital skills ##	-	-	-	-	-0.137 (0.010)***	-0.137 (0.010)***
Underrepresented women with AI-related digital skills ##	-	-	-	-	-0.097 (0.011)***	-0.102 (0.024)***
Experiment I###	-	-	-	-	0.049 (0.025)**	0.045 (0.025)*
Experiment II###	-	-	-	-	0.022 (0.026)	0.027 (0.026)
Experiment III###	-	-	-	-	0.049 (0.025)**	0.042 (0.026)
Underrepresented women with AI-related digital skills ## × Experiment I###	-	-	-	-	-	-0.008 (0.027)
Underrepresented women with AI-related digital skills## × Experiment II###	-	-	-	-	-	-0.026 (0.029)
Underrepresented women with AI-related digital skills## × Experiment III###	-	-	-	-	-	0.006 (0.031)
Wald x^2	99.53	120.20	81.22	129.42	260.53	265.72
Prob> x^2	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.189	0.108	0.100	0.181	0.075	0.075
Chi2′	1.71	4.51	7.81	10.49	20.22	2.18
Prob>chi2′	0.190	0.033	0.005	0.001	0.001	0.140
Observations	774	750	768	756	3,048	3,048

Notes: (^) The reference category is White women without AI-related digital skills. (^^) The reference category is younger women without AI-related digital skills. (^^^) The reference category is heterosexual women without AI-related digital skills. (#) The reference category is women without autism-spectrum disclosure and without AI-related digital skills. (##) The reference category is majority women without AI-related digital skills. (###) The reference category is Experiment IV. (′) In Models I–V, the Wald test assesses equality of coefficients between underrepresented women without and with AI-related digital skills. In Model VI, the Wald test assesses the joint significance of the interaction terms between underrepresented women with AI-related digital skills and Experiments I, II and III, with Experiment IV serving as the reference category. The table reports average marginal effects from probit models for main effects. Interaction effects are computed from predicted probabilities as differences in average predicted probabilities across the relevant treatment combinations, averaged over the observed covariate distribution. Experiment interactions compare the underrepresented-applicant versus majority-applicant interview invitation gap for the relevant signalling condition in Experiments I, II and III with the corresponding gap in Experiment IV, which serves as the reference experiment. All models control for firm sector, size, written EDI policies on the firm's website, the order in which job applications were sent and the type of application. Standard errors are clustered at the firm level. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 3. Probit Job Invitation Estimates (Marginal Effects): Heterogeneity by Sector, Firm Size, and Written EDI Policies

	Model I: Total	**Model II: Total**
Underrepresented women without AI-related digital skills ^	-0.135 (0.010)***	-0.144 (0.015)***
Underrepresented women with AI-related digital skills ^	0.006 (0.046)	-0.105 (0.016)***
Experiment I^^	0.049 (0.025)**	0.049 (0.025)*
Experiment II^^	0.022 (0.025)	0.022 (0.026)
Experiment III^^	0.049 (0.024)**	0.049 (0.025)**
Underrepresented women with AI-related digital skills ^ × Retail Sales and Customer Service^^^	-0.172 (0.058)***	-
Underrepresented women with AI-related digital skills^ × Hospitality and Front-of-House^^^	-0.147 (0.057)**	-
Underrepresented women with AI-related digital skills^ × Facilities and Logistics Support^^^	-0.127 (0.056)*	-
Underrepresented women with AI-related digital skills^ × Construction and Trades Support^^^	-0.069 (0.058)	-
Underrepresented women with AI-related digital skills^ × Education and Youth Programme Support^^^	-0.078 (0.063)	-
Underrepresented women with AI-related digital skills^ × Transport, Delivery and Dispatch^^^	-0.085 (0.063)	-
Underrepresented women with AI-related digital skills^ × Stock and Inventory Control^^^	-0.158 (0.065)**	-
Underrepresented women with AI-related digital skills^ × Administrative Support^^^	-0.108 (0.066)	-
Underrepresented women with AI-related digital skills^ × Finance and Payment Processing^^^	-0.196 (0.063)***	-
Underrepresented women without AI-related digital skills^ × Written EDI policies	-	0.003 (0.026)
Underrepresented women with AI-related digital skills^ ×Written EDI policies	-	0.007 (0.030)
Underrepresented women without AI-related digital skills^ × Firm size	-	0.015 (0.025)
Underrepresented women with AI-related digital skills^ × Firm size	-	0.016 (0.029)
Wald x^2	277.79	265.36
Prob> x^2	0.000	0.000
Pseudo R^2	0.081	0.076
Chi2ʹ	9.59	11.00
Prob>chi2ʹ	0.002	0.001
Observations	3,048	3,048

Notes: (^) The reference category is majority women without AI-related digital skills. (^^) The reference category is Experiment IV. (^^^) The reference category is Digital and Marketing Support. (ʹ) Wald test for equality of coefficients between underrepresented women without and with AI-related digital skills. The table reports average marginal effects from probit models for main effects. Interaction effects are computed from predicted probabilities as differences in average predicted probabilities across the relevant treatment combinations, averaged over the observed covariate distribution. Sector interactions compare each sector with Digital and Marketing Support, the reference sector. Firm-size and written-EDI interactions compare the relevant interviews invitation gap across the two firm categories. All models control for firm sector, size, written EDI policies on the firm's website, the order in which job applications were sent and the type of application. Standard errors are clustered at the firm level. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 4. Heteroskedastic Probit Job Invitation Estimates: Variance Equation, Log Standard Deviation Parameters

	Total
Underrepresented women without AI-related digital skills ^	-1.476 (0.511)***
Underrepresented women with AI-related digital skills ^	-1.095 (0.505)**
Wald x^2	323.46
Prob> x^2	0.000
Log Pseudolikelihood	-1262.514
Chi2ˊ	13.52
Prob>chi2ˊ	0.001
Observations	3,048

Notes: The reported coefficients correspond to the log of the residual standard deviation (lnsigma). (^) The reference category is majority women without AI-related digital skills. (ˊ) Wald test for the joint null hypothesis that the lnsigma coefficients are equal to zero. The model controls for firm sector, size, written EDI policies on the firm's website, as well as the order in which job applications were sent and the type of application. The model reports clustered standard errors at the firm level. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level.

Table 5. OLS Advertised Wage-Sorting Estimates: Natural Logarithm of Hourly Wages for Vacancies with Interview Invitations					
	Model I: Race	**Model II: Age**	**Model III: Sexual orientation**	**Model IV: Autism-spectrum disclosure**	**Model V: Total**
Black women without AI-related digital skills ^	-0.043 (0.019)**	-	-	-	-
Black women with AI-related digital skills ^	-0.020 (0.010)*	-	-	-	-
Older women without AI-related digital skills ^^	-	-0.034 (0.016)**	-	-	-
Older women with AI-related digital skills ^^	-	-0.009 (0.013)	-	-	-
Lesbian women without AI-related digital skills ^^^	-	-	-0.051 (0.018)***	-	-
Lesbian women with AI-related digital skills ^^^	-	-	-0.031 (0.014)**	-	-
Women with autism spectrum disclosure and without AI-related digital skills #	-	-	-	-0.064 (0.020)***	-
Women with autism spectrum disclosure and with AI-related digital skills #	-	-	-	-0.045 (0.012)***	-
Underrepresented women without AI-related digital skills ##	-	-	-	-	-0.068 (0.012)***
Underrepresented women with AI-related digital skills ##	-	-	-	-	-0.041 (0.007)***
Experiment I###	-	-	-	-	-0.012 (0.014)
Experiment II###	-	-	-	-	-0.024 (0.014)*
Experiment III###	-	-	-	-	-0.006 (0.012)
F	5.42	3.83	2.77	5.66	6.07
Prob> F	0.000	0.000	0.002	0.000	0.000
R^2	0.421	0.625	0.372	0.523	0.287
Wald test (F)´	3.00	3.34	2.99	3.05	8.01
Prob> F´	0.091	0.074	0.089	0.086	0.005
Observations	79	71	97	77	324

Notes: The dependent variable is the natural logarithm of advertised hourly wages for vacancies in which applicants were invited to interview. (^) The reference category is White women without AI-related digital skills. (^^) The reference category is younger women without AI-related digital skills. (^^^) The reference category is heterosexual women without AI-related digital skills. (#) The reference category is women without autism spectrum disclosure and without AI-related digital skills. (##) The reference category is majority women without AI-related digital skills. (###) The reference category is Experiment IV. (´) Wald test for equality of coefficients between underrepresented women without and with AI-related digital skills. All models control for firm sector, size, written EDI policies on the firm's website, as well as the order in which job applications were sent and the type of application. All models report clustered standard errors at the firm level. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Supplementary Appendix

Table S1. Sectors, Sector Shares, Job Openings and Associated Work Tasks Included in Job Applications

Panel I: Sectors	**Panel II: Sector Share (%)**	**Panel III: Job Openings: Titles/Roles**	**Panel IV: Associated Work Tasks**
Retail Sales and Customer Service	7.57%	Sales Assistant; Point-of-Sale Operator; Customer Support Worker; Retail Associate	Serving customers and responding to enquiries; Processing sales at the point of sale; Restocking shelves and organising displays; Handling returns and exchanges; Monitoring stock levels and reporting shortages; Maintaining accurate sales and service records.
Hospitality and Front-of-House	10.92%	Hotel Receptionist; Booking Assistant; Front Desk Coordinator; Guest Relations Assistant	Managing guest check-ins and check-outs; Handling reservation enquiries; Providing information about services and facilities; Recording guest requests and feedback; Coordinating with housekeeping and maintenance teams; Maintaining front desk logs and booking records.
Facilities and Logistics Support	8.95%	Stockroom Assistant; Inventory Coordinator; Delivery Booking Assistant; Warehouse Support Worker	Checking and organising stock deliveries; Completing order-verification checks; Updating warehouse or facility records; Allocating goods for dispatch; Maintaining storage areas safely and efficiently; Coordinating delivery schedules with internal teams.
Construction and Trades Support	9.94%	Site Scheduler; Job Planner; Project Administration Assistant; Site Support Officer	Preparing site documentation and project files; Scheduling visits and coordinating suppliers; Recording health and safety information; Logging daily site progress; Organising project-related paperwork; Assisting with procurement and delivery arrangements.
Education and Youth Programme Support	10.23%	Learning Support Worker; After-School Programme Assistant; Youth Administration Assistant; Classroom Support Assistant	Preparing learning or activity materials; Tracking attendance and participation; Assisting with classroom or activity supervision; Communicating with parents or guardians; Recording pupil information and progress notes; Supporting the organisation of daily sessions.
Transport, Delivery and Dispatch	11.02%	Route Planner; Dispatch Clerk; Courier Administration Assistant; Logistics Support Assistant	Scheduling deliveries and planning routes; Checking delivery documentation; Communicating with drivers and couriers; Updating dispatch records; Tracking deliveries and reporting issues; Coordinating booking slots for collections or drop-offs.
Stock and Inventory Control	10.03%	Warehouse Clerk; Storekeeper; Inventory Assistant; Stock Control Officer	Counting and verifying inventory; Restocking and organising storage areas; Completing quality checks on items; Updating stock control systems; Monitoring low-stock alerts; Preparing inventory reports and documentation.
Administrative Support	10.82%	Office Assistant; Records Clerk; Scheduling Assistant; Administrative Coordinator	Managing filing and digital records; Coordinating calendars and scheduling meetings; Handling incoming and outgoing communications; Preparing documents and correspondence; Maintaining office logs and registers; Supporting general office operations.
Finance and Payment Processing	11.71%	Junior Accounts Clerk; Invoicing Assistant; Payment Processing Worker; Accounts Support Assistant	Preparing and processing invoices; Recording financial transactions; Organising financial documentation; Tracking payments and outstanding balances; Reconciling daily or weekly records; Supporting routine bookkeeping duties.
Digital and Marketing Support	8.75%	Social Media Scheduler; Promotions Assistant; E-commerce Support Worker; Digital Content Assistant	Scheduling digital content and posts; Responding to online messages and comments; Updating website or platform listings; Preparing simple promotional materials; Reviewing basic analytics data; Supporting online engagement tasks.

Supplementary Appendix

Table S2. Training and Skills Included in Job Applications of Underrepresented Groups with AI-Related Digital Skills

Panel I: Sectors	Panel II: Training Included in Job Applications	Panel III: AI-Related Digital Skills Included in Job Applications
Retail Sales and Customer Service	Certificate in AI for Retail Customer Care: The course provided training in AI-assisted customer-interaction tools, digital product-awareness platforms, and automated point-of-sale accuracy systems.	Managing customer enquiries using AI-supported communication tools; Checking stock levels with AI-driven inventory systems; Processing sales through AI-enabled point-of-sale platforms; Providing product information using AI-generated catalogues.
Hospitality and Front-of-House	Certificate in AI for Front-of-House Service Operations: The course covered AI-enabled guest-communication tools, digital reservation-management systems, and automated front desk support platforms.	Handling guest enquiries through AI-assisted service dashboards; Managing reservations using AI-enabled booking systems; Coordinating front desk tasks with AI-supported scheduling tools; Recording guest feedback using AI-driven sentiment tools.
Facilities and Logistics Support	Certificate in AI for Logistics Support and Workplace Coordination: The course introduced AI-assisted stock-handling tools, automated order-checking systems, and digital delivery-coordination platforms.	Completing order-checks using AI-based verification systems; Coordinating delivery tasks through AI-assisted routing platforms; Updating warehouse records with AI-enabled data-entry tools; Monitoring stock flow using AI-driven optimisation dashboards.
Construction and Trades Support	Certificate in AI for Construction Administration Support: The course included training in AI-assisted site-documentation systems, automated supplier-scheduling tools, and digital health-and-safety recording platforms.	Managing site documents through AI-enabled document-processing tools; Coordinating suppliers using AI-assisted scheduling systems; Recording safety information with AI-supported compliance tools; Tracking project updates using AI-based workflow platforms.
Education and Youth Programme Support	Certificate in AI for Learning Support and Programme Coordination: The course focused on digital session-preparation tools, AI-enabled attendance-tracking systems, and guided communication platforms for parents.	Tracking attendance using AI-supported digital registers; Preparing learning materials with AI-assisted content tools; Communicating with parents through AI-enabled messaging systems; Recording pupil information using AI-driven administrative tools.
Transport, Delivery and Dispatch	Certificate in AI for Transport and Dispatch Administration: The course provided training in AI-enabled delivery-scheduling systems, automated route-documentation tools, and digital dispatch-coordination platforms.	Scheduling deliveries with AI-enabled routing systems; Updating dispatch records using AI-assisted documentation tools; Communicating with drivers through AI-supported platforms; Monitoring deliveries using AI-driven tracking dashboards.
Stock and Inventory Control	Certificate in AI for Stock Handling and Inventory Procedures: The course covered AI-assisted restocking systems, computer-vision tools for quality checking, and digital inventory-record platforms.	Performing stock checks with AI-supported scanning tools; Identifying product issues using AI-enabled visual-recognition systems; Updating stock logs through AI-assisted inventory platforms; Planning restocking using AI-driven prediction tools.
Administrative Support	Certificate in AI for Office and Administrative Procedures: The course offered training in workflow-automation tools, AI-enabled document-processing systems, and digital calendar-coordination platforms.	Organising documents using AI-enabled filing systems; Coordinating schedules with AI-assisted calendar tools; Processing internal information using AI-supported communication systems; Preparing documents with AI-driven drafting tools.
Finance and Payment Processing	Certificate in AI for Financial Administration Support: The course introduced automated invoice-processing tools, AI-enabled receipt-reading systems, and digital financial-record platforms.	Preparing invoices with AI-assisted processing tools; Reconciling payments using AI-driven financial dashboards; Recording financial data through AI-enabled bookkeeping systems; Checking receipts using AI-supported scanning tools.
Digital and Marketing Support	Certificate in AI for Digital Workplace Communication: The course covered AI-assisted online-communication tools, automated content-scheduling systems, and digital message management platforms.	Scheduling online content using AI-enabled planning tools; Responding to messages through AI-assisted communication dashboards; Reviewing analytics using AI-driven insight platforms; Drafting promotional text with AI-supported content-creation tools.

Supplementary Appendix

Table S3. Training and Skills Included in Job Applications of Majority and Underrepresented Groups without AI-Related Digital Skills

Panel I: Sectors	**Panel II: Training Included in Job Applications**	**Panel III: Work Skills Included in Job Applications**
Retail Sales and Customer Service	Certificate in Retail Customer Care: The course covered customer interaction practices, product awareness, and point-of-sale accuracy.	Customer interaction practices; Product awareness; Point-of-sale accuracy; Stock checking and labelling.
Hospitality and Front-of-House	Certificate in Front-of-House Service Operations: The course offered practical training in guest communication, reservation handling, and front-desk etiquette.	Guest communication; Reservation handling; Front-desk etiquette; Enquiry management.
Facilities and Logistics Support	Certificate in Logistics Support and Workplace Coordination: The course introduced stock handling, order-checking, and coordination of delivery activities.	Stock handling; Order-checking; Coordination of delivery activities; Updating workplace records.
Construction and Trades Support	Certificate in Construction Administration Support: The course involved training in site documentation, scheduling suppliers, and health-and-safety recording.	Site documentation; Scheduling suppliers; Health-and-safety recording; Maintaining project logs.
Education and Youth Programme Support	Certificate in Learning Support and Programme Coordination: The course focused on session preparation, attendance tracking, and communication with parents.	Session preparation; Attendance tracking; Communication with parents; Recording pupil information.
Transport, Delivery and Dispatch	Certificate in Transport and Dispatch Administration: The course provided training in delivery scheduling, route documentation, and dispatch coordination.	Delivery scheduling; Route documentation; Dispatch coordination; Updating transport records.
Stock and Inventory Control	Certificate in Stock Handling and Inventory Procedures: The course covered restocking processes, quality checking, and maintaining accurate inventory records.	Restocking processes; Quality checking; Maintaining accurate inventory records; Stock counting.
Administrative Support	Certificate in Office and Administrative Procedures: The course introduced filing systems, calendar coordination, and internal communication protocols.	Filing systems; Calendar coordination; Internal communication protocols; Preparing documents.
Finance and Payment Processing	Certificate in Financial Administration Support: The course covered invoice preparation, bookkeeping processes, and financial-record organisation.	Invoice preparation; Bookkeeping processes; Financial-record organisation; Payment tracking.
Digital and Marketing Support	Certificate in Digital Workplace Communication: The course introduced online communication practices, content scheduling, and message handling routines.	Online communication practices; Content scheduling; Message handling routines; Updating digital information.

Supplementary Appendix

Table S4. Sample Job Applications for the Majority Group and Underrepresented Groups with and without AI-Related Digital Skills

	Panel I: White British without AI-related digital skills	**Panel II: Black British without AI-related digital skills**	**Panel III: Black British with AI-related digital skills**
Email Communication			
	Subject: Application for Invoicing Assistant Position Dear Hiring Manager, I am writing to apply for the Invoicing Assistant vacancy advertised. Please find attached my application letter and CV. Thank you for considering my application. Yours sincerely, Emily Harper	Subject: Interest in the Invoicing Assistant Role Dear Recruitment Team, I wish to apply for the Invoicing Assistant role advertised. My application letter and CV are attached. Thank you for considering my application. Yours sincerely, Sophie Grant	Subject: Submission for Invoicing Assistant Position Dear Selection Panel, I am contacting you regarding the Invoicing Assistant vacancy currently advertised. Please see my attached application letter and CV. I appreciate your time and consideration. Yours sincerely, Hannah Lewis
Application Letters			
	Dear Hiring Manager, I am writing to express my interest in the Invoicing Assistant position. My background is in finance-related administrative work, including invoice preparation, document checking, and payment recording. In these roles, I have developed an efficient working style and adopted creative approaches to managing routine administrative and financial tasks. Additional information is included in my CV. Yours sincerely, Emily Harper	Dear Recruitment Team, I am contacting you regarding the Invoicing Assistant position. Over recent years, I have worked in finance-focused administrative roles involving invoice processing, payment documentation, and record organisation. Through this experience, I have developed an efficient working style in busy environments and applied creative problem-solving to support accurate and reliable administrative practices. A full overview of my experience is provided in my CV. Yours sincerely, Sophie Grant	Dear Selection Panel, I am writing to apply for the Invoicing Assistant position. My professional experience includes administrative roles within finance, involving handling invoices, checking financial documents, and monitoring payments. Across these roles, I have maintained efficient working habits and applied creative organisational methods to support reliable administrative and financial procedures. More details about my background can be found in my CV. Yours sincerely, Hannah Lewis
CVs			
	Name: Emily Harper Nationality: White British Date of Birth: 12 March 1997 Mobile: Email: Address: Professional Summary With a background in finance-oriented administration, I have worked on a range of tasks including preparing invoices, maintaining payment records, and supporting day-to-day	Sophie Grant Date of Birth: 18 May 1997 Black British Address: Mobile: Email: Personal Profile I am an experienced administrative worker with several years in finance-related roles, covering invoice processing, financial data entry, payment	Name: Hannah Lewis Email: Nationality: Black British Date of Birth: 12 March 1997 Mobile: Address: Profile Statement My experience spans multiple finance administration positions where I have managed invoices, recorded transactions, organised financial paperwork, and

bookkeeping. My experience also includes managing financial documentation and assisting with regular reconciliation activities. These responsibilities have helped me develop a well-organised approach and flexible methods for handling routine administrative and financial processes efficiently.

Academic Background

BTEC Level 3 in Business Administration
2015–2017

Apprenticeship in Business
2016–2017

Practical Training

2024 – Certificate in Financial Administration Support

- The course provided training in invoice handling, core bookkeeping duties, and the maintenance of financial documentation.
- I gained skills relevant to day-to-day finance operations, including preparing and issuing invoices, completing routine bookkeeping tasks, organising financial records for audit and reporting purposes, and monitoring payment activity to support smooth financial workflows.

Work History

Finance Support Assistant – [Employer 1], London
2020–2024

- Preparing and processing invoices
- Recording financial transactions
- Organising financial documentation

Administrative Assistant – [Employer 2], London
2017–2020

- Tracking payments and outstanding balances
- Reconciling daily or weekly records
- Supporting routine bookkeeping duties

tracking, and the organisation of financial records. I have contributed to reconciliation routines and general bookkeeping support, developing an efficient and dependable working style suited to busy environments. I rely on practical problem-solving skills to ensure accuracy and consistent administrative performance.

Learning and Qualifications

Business Administration Apprenticeship
2016–2017

BTEC Level 3 in Business Administration
2015–2017

Professional Development

Certificate in Financial Administration Support – 2024

- The course included invoice preparation, bookkeeping processes, and financial-record organisation.
- I developed workplace-ready finance skills, such as preparing invoices for routine operations, handling daily bookkeeping activities, maintaining organised financial files for business oversight, and tracking payments to ensure smooth accounting procedures.

Career Experience

Role: Financial Administrative Support – [Employer 1], London
2020–2024

- Maintaining accurate payment records and outstanding balances
- Preparing and issuing invoices
- Updating day-to-day financial entries

Role: Office Administration Assistant – [Employer 2], London
2017–2020

- Reconciling weekly or daily accounts
- Managing and organising finance-related documents
- Assisting with regular bookkeeping tasks

monitored payment activity. I have also supported routine bookkeeping and reconciliation processes, establishing effective working habits and structured organisational techniques. In addition, I bring practical knowledge of AI-supported tools commonly used in administrative and accounting tasks.

Education

2015–2017 – BTEC Level 3 in Business Administration

2016–2017 – Business Administration Apprenticeship

Specialist Training

Certificate in AI for Financial Administration Support (2024)

- The course introduced automated invoice-processing tools, AI-enabled receipt-reading systems, and digital financial-record platforms.
- I developed practical finance skills using AI-based tools, including generating invoices through automated systems, reviewing and validating receipts with AI-supported scanners, entering financial information into AI-enhanced bookkeeping platforms, and reconciling payment activity through AI-driven accounting dashboards.

Employment Record

2020–2024 – Financial Support Officer, [Employer 1], London

- Handling invoice preparation and distribution
- Managing financial paperwork and record-keeping
- Monitoring payments and identifying overdue balances

2017–2020 – Administrative Services Assistant, [Employer 2], London

- Completing regular bookkeeping activities
- Entering financial data into ledgers
- Carrying out account reconciliation on a routine basis

	Additional Details Interests: I enjoy travelling, particularly exploring new places within the UK and abroad, and I also regularly go to the cinema, where I follow a range of recent films.	Interests and Activities I often visit the cinema to watch new releases. I enjoy travelling and learning about different destinations within the UK and overseas.	Personal Interests Outside work, I enjoy travelling, particularly exploring new cities and countries. I also attend the cinema regularly and follow new movies.